The Effect of Parental Involvement and its Associated Policies on Student Outcomes

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ABSTRACT

KRISTINA VAUGHAN: The Effect of Parental Involvement and its Associated Policies on Student Outcomes.
(Under the direction of David K. Guilkey and Jane Cooley-Fruehwirth)

In an effort to get parents more involved in their child's schooling, 14 states have implemented a policy and a further four states have pending bills that would allow parents time off from their place of work to participate in their child's schooling. In the first chapter, I examine the effect of these school-related leave policies on cognitive and non-cognitive outcomes, and identify some potential mechanisms through which these policies can operate. I find evidence that the policy affects math skills, whereby an additional hour off of work leads to a 0.005 standard deviation increase in math skills. I identify increases in the probability of volunteering, attending a back school night, and maternal employment and home inputs as potential mechanisms for this effect.

Despite recent state and federal initiatives emphasizing parental involvement in schools as a way to improve child outcomes, there is little empirical evidence of the effects of parental involvement, largely due to the empirical challenges involved in establishing causality. In the second chapter, I study the effects of parental involvement on cognitive and non-cognitive outcomes as students progress through school. I address key challenges in the literature such as the non-random nature of parental involvement and the exclusion of related input decisions such as home inputs, employment, and fertility decisions that have the potential to affect and be affected by parental involvement with ambiguous effects on child skill development. After addressing these sources of bias, I find positive effects of volunteering in school on math, reading, and non-cognitive skills comparable to 19%, 17%, and 64% of the direct effect of a mother having a bachelor's degree or higher, respectively. I find evidence of positive spillovers of parental involvement to other inputs, most notably home inputs, that have positive effects on child skill formation. Using the estimated model, I simulate the effect of existing state-level policies that allow parents time off from their

place of work to participate in their child's schooling. I find that allowing parents the maximum of 40 hours off per year to participate in their child's school leads to increases in non-cognitive skills over the life-cycle of the child, primarily through increasing the level of volunteering.

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CHAPTER 1

THE EFFECT OF STATE SCHOOL-RELATED LEAVE POLICIES ON STUDENT OUTCOMES

1.1 Introduction

Recent federal acts such as the current 2015 Every Student Succeeds Act and the preceding 2001 No Child Left Behind Act emphasize interactions between parents and teachers as a means to improving student outcomes. Given the national priority of fostering greater contact between parents and teachers, states themselves have taken the initiative to find innovative ways to get parents involved in their child's schooling. One such way in which states have sought to facilitate greater contact between parents and teachers is through the implementation of employment-based policies that allow parents time off from their place of work to participate in their child's schooling, geared at alleviating potentially binding work constraints. At the time of writing, 14 states had the policy in place and a further 4 states had pending bills to implement the policy. The impacts of the policy are potentially far-reaching. In 2017, 33.6 million families, or approximately 45% of all families had children under 18 and of these families, 90.7% had at least one employed parent, indicating that the vast majority of parents with school-aged children were employed. Despite the relatively widespread implementation of the policy and the potential wide reaching impacts, as yet, the effects of the policy have not yet been formally quantified. Using a large nationally representative survey, this paper evaluates the total effects of these state school-related leave policies on the cognitive and non-cognitive outcomes of elementary school students and examines some of the mechanisms through which the policies can affects outcomes.

I examine the total effect of the policy by regressing measures of cognitive and non-cognitive outcomes on the state school-related leave policies and a vector of individual, household and state characteristics, and grade (time) fixed effects to control for the effect of potentially confounding variables. I provide some evidence to show that the policy is not reflecting the effect of other related state characteristics by controlling for a rich set of state-level characteristics directly in the model. Another concern with estimating the effect of the policy is the potential for states that have policy to differ systematically in some unobserved way that causes these states to also have children with higher or lower test scores, leading to inconsistent estimates of the effect of the policy. In lieu of state fixed effects, I provide statistical evidence that this source of endogeneity is unlikely to be a concern by evaluating average math and reading test scores in states that do and do not have the policy in the pre-policy period and using a statistical test of the equality of means to determine that these states do not have statistically different average test scores.

I find evidence of a positive total effect of the policy on math skills where a 1 hour increase in the time parents are allowed off of work leads to a 0.005 standard deviation increase in math skills. Interestingly, I find weak evidence of a negative effect of the policy on non-cognitive skills where a 1 standard deviation increase in the policy leads to a decrease of 0.002 standard deviations in non-cognitive skills, though only at the 10% level. I find some evidence of heterogeneity in the effect of the policy on math skills, most notably lesser effects for Hispanic individuals for math skills, and negative effects for individuals who do not speak English as the primary language at home for reading and non-cognitive skills. Despite finding negative effects for individuals who do not speak English as the primary language at home, I do not find evidence that the negative effects are coming through the mechanisms explored in this paper. I also find evidence that the policy matters more for individuals in later grades, and find some evidence to suggest that this is due to the propensity for mothers to be more likely to be employed in these later grades. Interestingly, whereas I do not find effects of reading scores in the baseline model, when I analyse differential effects of the policy by grade, I find a positive effect of the policy on reading scores in grade 2.

I also examine some mechanisms through which the policy could be affecting outcomes based on what has previously been discussed in the literature. Given that the policy is targeted at increasing parental participation in school-based activities, I examine the effect of the policy along various dimensions of parental involvement: the probability of volunteering, attending a parent-teacher conference, attending a back to school night, attending a school event, and attending a parent-teacher organization or association meeting. I find that the policy positively affects the probability of volunteering, attending a parent-teacher conference, and attending a back to school night. Conversely, I find that the policy has a negative effect on the probability of attending a PTA/PTO meeting. Given the theoretical evidence that parental involvement can affect the quantity and quality of home inputs (Wherry (2004)), and the potential for maternal employment to be affected by the policy through making work more attractive, or other indirect channels, I also examine whether the policy affects home inputs and maternal employment. I find positive effects of the policy on both maternal employment and home inputs whereby a 1 hour increase in the number of hours of school-related leave leads to a 0.006 per cent increase in the probability of maternal employment and a 0.005 standard deviation increase in the level of home inputs. I also explore heterogeneity in the effects of the policy on the above mechanisms but do not find much evidence of heterogeneous effects.

My main contribution to the existing literature is providing the first evaluation of the effects of these existing state school-related leave policies and examining some of the mechanisms through which these policies can affect outcomes. To the best of my knowledge, I am aware of one other paper that adopts a somewhat similar approach. Avvisati (2013) exploit a randomized experiment in French middle schools that randomized parents of sixth graders into meetings at school with the school head to discuss strategies on how best to support and monitor children with their school work. The authors found that the intervention increased parent's participation in both school-based and home-based activities which translated into improvements in behaviour such as a reduction in truancy and disciplinary sanctions, but did not find evidence of an improvement in test scores. My research differs from the previous study along three dimensions: First, unlike the previous intervention which only considered the effects of interactions between parents and the school head, the policy has the potential to affect more general forms of parental involvement including interactions between parents and teachers. One might expect that these two types of interactions may have different effects as teachers may be better able to give individualized advice tailored to each student whereas the school head is likely to be able to only give general advice. This difference in the level of interaction could explain why Avvisati (2013) found no evidence of an effect of the policy on test scores. Second, in contrast to the previous study that was conducted in middle school, I focus on elementary school students. Previous research has shown that parental involvement matters more earlier on in a child's life, hence we might expect different effects in elementary and middle school. Last, I evaluate the effect of an employment-based policy which may have different mechanisms than the randomized experiment. For instance, we might expect both interventions to affect the level of parental involvement and possibly home inputs, but there might be additional effects of the employment-based policy such as inducing women to work by making work more attractive that may have additional effects on child skill formation.

The rest of the paper proceeds as follows, Section 1.2 discusses the data to be used in the estimation and why it is well-suited for this analysis. Section 1.3 gives the empirical specification, discussing estimation and identification. Section 1.4 gives results and Section 1.5 concludes.

1.2 Data

The dataset used for this analysis is the Early Childhood Longitudinal Study, Kindergarten Class (ECLS-K), a nationally representative sample of kindergarteners in the United States who began kindergarten in the fall of 2010. The ECLS-K is a longitudinal survey of children, including detailed information on their parents, schools and teachers. The survey collects information on home and school inputs, in addition to cognitive and non-cognitive measures for children, making the dataset well-suited to this analysis. The restricted use ECLS-K dataset contains information on the state of residence of the child, allowing the dataset to be merged with state employment legislation that dictates the number of hours of school-related leave a parent is allowed off. There are currently four main waves of data: the fall (2010) and spring (2011) of kindergarten, the spring of grade 1 (2012),[1] the spring of grade 2 (2013), and the spring of grade 3 (2014) with the spring of grades 4 (2015) and 5 (2016) forthcoming. For the purposes of this analysis, I use the spring of grade 1, the spring of grade 2 and the spring of grade 3 waves.

I define my measures of parental involvement using 5 binary variables: the probability of volunteering, attending a parent-teacher conference, attending a back to school night, attending a school event, and attending a Parent-Teacher Organization (PTO) or Parent-Teacher Association

[1] A small sub-sample of the children were surveyed in the fall of grade 1 and the fall of grade 2.

(PTA) meeting. Summary statistics for the variables are presented in Appendix table A.1.3.

I define home inputs as activities parents partake in with their children outside the realm of the school.[2] The construct of home inputs is the simple average of four variables: the frequency the child reads books, whether the child participates in extra-curricular activities, whether the number of hours of TV watched on a weekday is above or below the sample median, and how often the family eats dinner together.[3] The average of the standardized home input index and summary statistics of the variables used to construct the index are presented in Appendix table A.1.3.

Non-cognitive skills are extracted as a latent factor from the following teacher-reported measures: Approaches to learning, Self-control, Inter-personal skills, Externalizing and Internalizing problem behaviours, Inhibitory Control and Attentional Focus. I aggregate these measures into a single index using polychoric analysis for convenience and to reduce the number of parameters to be estimated. I outline the procedure used to aggregate the non-cognitive scores in section A.2.1 of the appendix. The factor loadings associated with these variables are shown in Appendix Table F.2.5. Approaches to Learning and Self-control are the variables that load most highly onto the non-cognitive factor across all four waves.

Cognitive skills are measured by Item Response Theory (IRT) math and reading scores based on standardized cognitive tests collected as part of the ECLS-K survey. I discuss the advantages of using IRT test scores in section A.2.1 of the appendix.

I present the summary statistics for the variables used in this analysis in Appendix tables A.1.1-A.1.4, and present the states with the number of hours in appendix table A.1.2 and the distribution

[2]One concern is that parental inputs at home and parental involvement at school may be both proxying for underlying latent parenting quality, however, I provide theoretical and empirical evidence that suggests the two are distinct constructs. Firstly, parental involvement at school is an established concept in the education literature, and is treated as a distinct concept from home inputs. Secondly, the theoretical existence of these as two separate dimensions of parental inputs is validated statistically as suggested by the presence of two distinct factors when all variables are put together, one that loads more on variables used in the construction of home inputs and one that loads more on variables used in the parental involvement measure. Lastly, the correlation between volunteering at school and home inputs is 0.13, 0.15, 0.14, and 0.16 across the four waves, and the correlation between attending a parent-teacher conference and home inputs are 0.04, 0.07, 0.06, and 0.06, a relatively lower degree of correlation than one would expect if the two measures were capturing the same underlying dimension of parenting skill.

[3]I constrained my construct to variables that were available across all four waves for consistency in interpretation of the construct.

of the hours of school-related leave in figure A.1.7.

1.3 Empirical Framework

The primary interest of this study is quantifying the total effect of existing state-level school-related leave policies on cognitive and non-cognitive outcomes. Of additional interest is the effect of the policy on potential mechanisms. I begin my analysis by specifying production functions for the cognitive and non-cognitive skills:

$$A^c_{ift} = \gamma^c_1 P_{ift} + \gamma^c_2 X_{ift} + \gamma^c_3 W_{ift} + \delta^c_t + \psi^c_{ift} \tag{1.1}$$

$$A^n_{ift} = \gamma^n_1 P_{ift} + \gamma^n_2 X_{ift} + \gamma^n_3 W_{ift} + \delta^n_t + \psi^n_{ift} \tag{1.2}$$

where i indexes individual, f indexes states, and t indexes year. The variables A^c_{ift} and A^n_{ift} are the cognitive and non-cognitive outcomes of interest. The variable P_{ift} represents the hours of school-related leave per state. The primary parameters of interest are γ^c_1 and γ^n_1, which give the direct effect of the policy on cognitive and non-cognitive skills, respectively. The vector X_{ift} captures exogenous characteristics and includes household income, the mother's age and age squared, family structure, the primary language spoken at home, the child's gender and race, and the mother's education status. The vector W_{ift} captures state-level characteristics such as the expenditure per pupil, state GDP per capita, the unemployment rate, the average weekly welfare benefit, and the average child tax credit. The term δ_t captures time/grade fixed effects and ψ_{ift} is an idiosyncratic error term.[4]

I maintain the same specifications to identify the effect of the policy on various mechanisms of

[4] Since this is a cohort study and I do not consider individuals who are retained, time fixed effects will be the same as grade fixed effects.

interest (M_{ift}):

$$M_{ift} = \alpha_1 P_{ift} + \alpha_2 X_{ift} + \alpha_3 W_{ift} + \delta_t + \zeta_{ift} \tag{1.3}$$

where the primary parameter of interest here is α_1.

Standard errors are clustered at the school level in all specifications to account for correlation in the error term across students in the same school.

1.3.1 Identification

As mentioned before, the primary parameters of interest are γ_1^c and γ_1^n, which give the total effect of the policy on cognitive and non-cognitive skills, respectively. One concern with estimating these parameters is that the state school-related leave policies could be correlated with other related state-level characteristics that can affect outcomes. For instance, one possibility is that states with more generous school-related leave policies are states that spend more on education. If spending more on education affects student outcomes, then the effect of the policy would be conflated with the effect of increased educational spending. I argue that controlling for a rich set of state characteristics, including education expenditure per pupil, in the term W_{ift} addresses this and other related concerns. A more challenging concern is that policy generosity might be correlated with unobserved state characteristics that are in turn correlated with child outcomes. For instance, states with more generous policies could be states that systematically have students that perform better or worse due to some unobserved state-level characteristics. Since the variation in the policy over time within the sample is not sufficient to accommodate state fixed effects, in order to give some indication as to whether this source of bias is likely to be of concern, I evaluate the differences in math and reading test scores in states that do and do not have the policy in the pre-policy period using data from the National Assessment of Educational Progress math and reading test scores and perform a t-test on the differences of means.[5] I discuss this test further in Appendix section B.1.1 and report the results in table 1.1, below. Based on the test statistics of the differences in means, the

[5]The data is provided by the National Center for Education Statistics.

probability that the difference is not equal to zero is rejected at conventional significance levels and the probability that math and reading scores are lower in states that have the policy is not rejected at the 10% level. The results indicate that if this form of bias is present, that the estimates would be biased downwards as states that have the policy tended to have individuals with lower math and reading test scores compared with individuals in states without the policy. Theoretically, the policy should be tested the policy along the intensive margin, however, data limitations precludes this. Analogous arguments can be made for recovering consistent estimates of the parameter α_1.

Table 1.1: Test of Equivalence of Means for Math and Reading Test Scores for States With and Without the Policy in the Pre-policy Period

	No Policy	Policy	Pr(diff < 0)	Pr(diff $\neq 0$)	Pr(diff > 0)
Math	219.70	215.08	0.93	0.15	0.05
	(7.67)	(9.35)			
Reading	216.73	211.83	0.92	0.15	0.08
	(7.19)	(10.30)			

1.4 Results

In table 1.2, I present the effects of the policies on the pooled sample of math, reading and non-cognitive skills. I find that allowing parents an additional hour off of work leads to a 0.005 standard deviation increase in a child's math skills. By contrast, I do not find direct effects of the policy on a child's reading skills and find weak evidence of a negative effect on the policy on non-cognitive skills of the magnitude of 0.002 standard deviations at the 10% significance level.

Since the index of non-cognitive skills could be masking differential effects of the policy by the individual components in the index, in table 1.3, I replace the index of non-cognitive skills with the individual skills comprising the index (See table F.2.5) and repeat the analysis. Column 1 reports approaches to learning, Column 2 reports self-control, Column 3 reports interpersonal skills, Column 4 reports externalizing behaviour, Column 5 reports internalizing behaviour, Column 6 reports attentional focus, and Column 7 reports inhibitory control. Based on the analysis, it appears there is variation in the effect of the policy across different measures of non-cognitive skills, though none reflect a positive effect. Specifically, the policy has a negative impact on approaches to learning, self-control and externalizing behaviour, the skill most associated with behavioural

Table 1.2: Reduced Form Effect of the State School-Related Leave Policy on Math, Reading and Non-Cognitive Scores

	(1) Math		(2) Reading		(3) Non-Cognitive	
Policy	0.0046^{***}	(0.0015)	-0.0007	(0.0015)	-0.0019^{*}	(0.0011)
Observations	21750		21750		21750	
R^2	0.48		0.41		0.13	

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors clustered at the school level are reported in parentheses. The full set of controls have been suppressed for brevity. The full set of controls are child gender, mother's age, mother's age squared, mother's education status, annual household income (000's), child race, family structure, primary language spoken at home, state-level expenditure per pupil, GDP per capita, the unemployment rate, the average weekly welfare benefit, the maximum number of weeks of welfare benefits, and the average unemployment insurance claims, and year dummies. * refers to statistical significance at the 10% level, ** refers to statistical significance at the 5% level, *** refers to statistical significance at the 1% level.

problems, which are all statistically significant at the 5% level. I find weak evidence of a negative effect of the policy on interpersonal skills and internalizing behaviours, and no effect of the policy on attentional focus and inhibitory control. Previous findings in the literature have documented a potential negative effect of parental involvement on non-cognitive skills through mechanisms such as reducing children's excitement about learning and psychological health, and increasing their stress levels (Kohn (2013)), that could be reflected in the negative effect observed here.

Table 1.3: Reduced Form Effect of the State School-Related Leave Policy on Different Components of Non-Cognitive Skills

	(1) App.	(2) Cont.	(3) Per.	(4) Ext.	(5) Int.	(6) Att.	(7) Inh.
Policy	-0.0028^{***}	-0.0023^{**}	-0.0022^{*}	-0.0026^{**}	-0.0018^{*}	-0.0006	-0.0008
	(0.0011)	(0.0012)	(0.0012)	(0.0010)	(0.0011)	(0.0011)	(0.0011)
Observations	21750	21750	21750	21750	21750	21750	21750
R^2	0.12	0.07	0.08	0.09	0.03	0.10	0.11

Notes: Column (1) reports approaches to learning, Column (2) reports self-control, Column (3) reports interpersonal skills, Column (4) reports externalizing behaviour, Column (5) reports internalizing behaviour, Column (6) reports attentional focus, and Column (7) reports inhibitory control. Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors clustered at the school level are reported in parentheses. The full set of controls have been suppressed for brevity. The full set of controls are child gender, mother's age, mother's age squared, mother's education status, annual household income (000's), child race, family structure, primary language spoken at home, state-level expenditure per pupil, GDP per capita, the unemployment rate, the average weekly welfare benefit, the maximum number of weeks of welfare benefits, and the average unemployment insurance claims, and year dummies. * refers to statistical significance at the 10% level, ** refers to statistical significance at the 5% level, *** refers to statistical significance at the 1% level.

Since it is possible that the policy could have positive effects that diminish as the number of hours allowed off increases, in table 1.4 I check for potential non-linearities in the effect of the policy by including the number of hours squared. I do not find any evidence to suggest that there are non-linear effects of the policy. I also experimented with a cubic specification (not shown) where I included the number of hours cubed, and did not find any evidence of non-linearities in that specification.

Table 1.4: Non-linearities in the Effect of the State School-Related Leave Policy on Math, Reading and Non-Cognitive Scores

	(1) Math		(2) Reading		(3) Non-Cognitive	
Policy	0.0052	(0.0054)	0.0018	(0.0042)	0.0018	(0.0032)
Policy squared	-0.0000	(0.0001)	-0.0001	(0.0001)	-0.0001	(0.0001)
Observations	21750		21750		21750	
R^2	0.48		0.41		0.13	

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors clustered at the school level are reported in parentheses. The full set of controls have been suppressed for brevity. The full set of controls are child gender, mother's age, mother's age squared, mother's education status, annual household income (000's), child race, family structure, primary language spoken at home, state-level expenditure per pupil, GDP per capita, the unemployment rate, the average weekly welfare benefit, the maximum number of weeks of welfare benefits, and the average unemployment insurance claims, and year dummies. * refers to statistical significance at the 10% level, ** refers to statistical significance at the 5% level, *** refers to statistical significance at the 1% level.

Pooling the sample could be masking important heterogeneity by grade (time). Such heterogeneity may be of interest to policy makers as it may reveal information about the effectiveness and/or uptake of the policy in different grades. In table 1.6, I check whether the policy has differential effects depending on the grade of the child by interacting the policy with grade fixed effects. I find that the policy has positive effects on math skills in grade 2 and grade 3, relative to grade 1. Interestingly, whereas I do not find an effect on reading skills in the baseline model, I find that the policy has positive effects on reading skills in grade 2, relative to grade 1. I do not find heterogeneous effects in non-cognitive skills by grade level. One hypothesis for why the effects of the policy are largely confined to later grades is that parents may be more likely to be employed in the child's later grades, hence the policy may have a greater effect on alleviating work constraints in these later grades. In order to test this hypothesis, I evaluate the determinants of maternal employment in table 1.6 including grade (time) fixed effects. As can be seen from the table, the mother is more likely to be employed, and thus potentially more time constrained, in grades 2 and 3, compared with grade 1, providing some support for this hypothesis.

Table 1.5: Heterogeneous Effects of the Policy on Outcomes by Grade (Time)

	(1) Math		(2) Reading		(3) Non-Cognitive	
Policy	0.0021	(0.0017)	−0.0019	(0.0014)	−0.0023**	(0.0011)
Policy*Grade 2	0.0051***	(0.0012)	0.0023**	(0.0011)	0.0013	(0.0011)
Policy*Grade 3	0.0028**	(0.0014)	0.0010	(0.0012)	0.0017	(0.0013)
Grade 2	1.2755***	(0.0230)	1.1142***	(0.0161)	−0.0118	(0.0177)
Grade 3	2.1290***	(0.0553)	1.8114***	(0.0211)	−0.0051	(0.0203)
Observations	21750		21750		21750	
R^2	0.48		0.41		0.13	

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors clustered at the school level are reported in parentheses. The full set of controls have been suppressed for brevity. The full set of controls are child gender, mother's age, mother's age squared, mother's education status, annual household income (000's), child race, family structure, primary language spoken at home, state-level expenditure per pupil, GDP per capita, the unemployment rate, the average weekly welfare benefit, the maximum number of weeks of welfare benefits, and the average unemployment insurance claims, and year dummies. * refers to statistical significance at the 10% level, ** refers to statistical significance at the 5% level, *** refers to statistical significance at the 1% level.

1.4.1 Heterogeneous Policy Effects

Prior to considering possible heterogeneous effects of the policy by different groups of individuals, it is first interesting to see which types of individuals could potentially disproportionately benefit from the policy based on their propensity for employment. In table 1.6, I regress maternal employment on a vector of exogenous characteristics to identify the most salient characteristics for employment. Older mothers, more educated mothers, wealthier mothers, and black mothers (compared with white mothers) are more likely to be employed. By contrast, mothers who do not speak English as the primary language at home, Hispanic mothers (compared with white mothers), and single parents are less likely to be employed. Guided by the key determinants of maternal employment, I examine whether there are heterogeneous effects of the policy by maternal education status, race, primary language spoken at home, income, which I demean in the interaction term for ease of interpretation, and family structure in tables 1.7-1.11 respectively.

In table 1.7, I find that the policy has negative effects on non-cognitive skills for mothers with

Table 1.6: Logit Equation of the Determinants of Maternal Employment

	(1) Maternal Employment	
Female	-0.0242	(0.0439)
Mother's Age	0.8748^{***}	(0.1901)
Mother's Age Sq.	-0.1145^{***}	(0.0259)
Some College	0.4351^{***}	(0.0551)
Bachelors or Higher	0.7685^{***}	(0.0642)
Household Income	0.2148^{***}	(0.0612)
Black	0.1855^{**}	(0.0877)
Hispanic	-0.1489^{**}	(0.0718)
Other	0.0510	(0.0811)
Single Parent	-0.5917^{***}	(0.0631)
Non-English Home Language	-0.3584^{***}	(0.0695)
Grade 2	0.1540^{***}	(0.0248)
Grade 3	0.2665^{***}	(0.0323)
Constant	-1.3988^{***}	(0.3552)
Observations	21750	

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors clustered at the school level are reported in parentheses. * refers to statistical significance at the 10% level, ** refers to statistical significance at the 5% level, *** refers to statistical significance at the 1% level.

some college or a bachelors or higher education relative to high school or less than high school, potentially due to the reasons discussed previously. By contrast, with the exception of a weakly positive effect of the policy for mothers with some college education relative to high school or less than high school, I do not find evidence of policy heterogeneity for math and reading test scores.

Table 1.7: Heterogeneous Effects of the Policy on Outcomes by Education Status

	(1)		(2)		(3)	
	Math		Reading		Non-Cognitive	
Policy	0.0029	(0.0020)	−0.0008	(0.0021)	0.0006	(0.0013)
Policy*College	0.0043*	(0.0022)	0.0014	(0.0024)	−0.0035**	(0.0016)
Policy*Bachelors	0.0014	(0.0025)	−0.0005	(0.0025)	−0.0041**	(0.0017)
Some College	0.2537***	(0.0400)	0.2946***	(0.0374)	0.0841***	(0.0268)
Bachelors or Higher	0.6165***	(0.0425)	0.6543***	(0.0393)	0.2583***	(0.0295)
Observations	21750		21750		21750	
R^2	0.48		0.41		0.13	

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors clustered at the school level are reported in parentheses. The full set of controls have been suppressed for brevity. The full set of controls are child gender, mother's age, mother's age squared, mother's education status, annual household income (000's), child race, family structure, primary language spoken at home, state-level expenditure per pupil, GDP per capita, the unemployment rate, the average weekly welfare benefit, the maximum number of weeks of welfare benefits, and the average unemployment insurance claims, and year dummies. * refers to statistical significance at the 10% level, ** refers to statistical significance at the 5% level, *** refers to statistical significance at the 1% level.

In table 1.8, I show that the effect of the policy is less effective for math skills for Hispanic children but do not find differential effects by race for black children or children from other races. A lesser effect of the policy by race could be explained by racial differences in the propensity to be employed, barriers to involvement, perhaps linguistic, (Aronson (1996)) given the high degree of correlation between Hispanic children and a not speaking English as the primary language at home of about 0.51, preferences for child skill, and/or returns to child skill. Another potential explanation that has been suggested in the literature is a cultural reluctance to interfere in what is viewed as the domain of teachers (Lareau (2000)). When examining heterogeneity by the primary language spoken at home in table 1.9, I find that the policy has negative effects on reading skills and non-cognitive skills, but not math skills. In section 1.4.2, I examine whether evidence of policy heterogeneity on mechanisms can help to explain these heterogeneous effects.

Table 1.8: Heterogeneous Effects of the Policy on Outcomes by Race

	(1) Math		(2) Reading		(3) Non-Cognitive	
Policy	0.0071***	(0.0019)	0.0010	(0.0021)	−0.0010	(0.0016)
Policy*Black	0.0075	(0.0050)	0.0069	(0.0052)	−0.0020	(0.0036)
Policy*Hispanic	−0.0069***	(0.0024)	−0.0039	(0.0025)	−0.0003	(0.0018)
Policy*Other	−0.0009	(0.0027)	−0.0019	(0.0027)	−0.0033	(0.0020)
Black	−0.7252***	(0.0507)	−0.2943***	(0.0505)	−0.1818***	(0.0388)
Hispanic	−0.3388***	(0.0459)	−0.1969***	(0.0444)	0.0238	(0.0319)
Other	0.1108**	(0.0501)	0.1885***	(0.0449)	0.1521***	(0.0337)
Observations	21750		21750		21750	
R^2	0.48		0.41		0.13	

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors clustered at the school level are reported in parentheses. The full set of controls have been suppressed for brevity. The full set of controls are child gender, mother's age, mother's age squared, mother's education status, annual household income (000's), child race, family structure, primary language spoken at home and year dummies. * refers to statistical significance at the 10% level, ** refers to statistical significance at the 5% level, *** refers to statistical significance at the 1% level.

Table 1.9: Heterogeneous Effects of the Policy on Outcomes by Primary Language Spoken at Home

	(1) Math		(2) Reading		(3) Non-Cognitive	
Policy	0.0066***	(0.0016)	0.0010	(0.0016)	−0.0008	(0.0013)
Policy*Non-English	−0.0059***	(0.0021)	−0.0049**	(0.0020)	−0.0033**	(0.0015)
Non-English Home Language	0.0175	(0.0477)	−0.1543***	(0.0474)	0.1917***	(0.0341)
Observations	21750		21750		21750	
R^2	0.48		0.41		0.13	

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors clustered at the school level are reported in parentheses. The full set of controls have been suppressed for brevity. The full set of controls are child gender, mother's age, mother's age squared, mother's education status, annual household income (000's), child race, family structure, primary language spoken at home, state-level expenditure per pupil, GDP per capita, the unemployment rate, the average weekly welfare benefit, the maximum number of weeks of welfare benefits, and the average unemployment insurance claims, and year dummies. * refers to statistical significance at the 10% level, ** refers to statistical significance at the 5% level, *** refers to statistical significance at the 1% level.

Interestingly, despite the propensity for wealthier households to be more likely to be employed, when analyzing the results in table 1.10, I do not find heterogeneous effects of the policy by household income. In table 1.11, I also do not find evidence of heterogeneity in the policy by family structure, despite single parents having a lower probability of being employed.

Table 1.10: Heterogeneous Effects of the Policy on Outcomes by Household Income

	(1) Math		(2) Reading		(3) Non-Cognitive	
Policy	0.0046***	(0.0015)	−0.0007	(0.0015)	−0.0019*	(0.0011)
Policy*Income	0.0014	(0.0016)	0.0012	(0.0014)	−0.0009	(0.0013)
Household Income	0.3233***	(0.0314)	0.2671***	(0.0298)	0.1497***	(0.0227)
Observations	21750		21750		21750	
R^2	0.48		0.41		0.13	

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors clustered at the school level are reported in parentheses. The full set of controls have been suppressed for brevity. The full set of controls are child gender, mother's age, mother's age squared, mother's education status, annual household income (000's), child race, family structure, primary language spoken at home, state-level expenditure per pupil, GDP per capita, the unemployment rate, the average weekly welfare benefit, the maximum number of weeks of welfare benefits, and the average unemployment insurance claims, and year dummies. * refers to statistical significance at the 10% level, ** refers to statistical significance at the 5% level, *** refers to statistical significance at the 1% level.

Table 1.11: Heterogeneous Effects of the Policy on Outcomes by Family Structure

	(1) Math		(2) Reading		(3) Non-Cognitive	
Policy	0.0033	(0.0026)	−0.0004	(0.0027)	−0.0024	(0.0017)
Policy*Single Parent	0.0015	(0.0025)	−0.0003	(0.0024)	0.0006	(0.0016)
Single Parent	0.0942**	(0.0401)	0.1433***	(0.0392)	0.2577***	(0.0289)
Observations	21750		21750		21750	
R^2	0.48		0.41		0.13	

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors clustered at the school level are reported in parentheses. The full set of controls have been suppressed for brevity. The full set of controls are child gender, mother's age, mother's age squared, mother's education status, annual household income (000's), child race, family structure, primary language spoken at home, state-level expenditure per pupil, GDP per capita, the unemployment rate, the average weekly welfare benefit, the maximum number of weeks of welfare benefits, and the average unemployment insurance claims, and year dummies. * refers to statistical significance at the 10% level, ** refers to statistical significance at the 5% level, *** refers to statistical significance at the 1% level.

1.4.2 Mechanisms

The baseline results show a positive effect of the policy on math scores. In this section, I evaluate potential mechanisms through which these policies can affect math scores according to the empirical specification in equation 1.3. Since the policy is specifically targeted at parental participation in school-based activities, I evaluate the effect of the policies on different types of parental involvement, namely, the probability of volunteering, the probability of attending a parent-teacher conference, the probability of attending a back to school night, the probability of attending a school event, and the probability of attending a parent-teacher organization or association meeting. I also consider other potential mechanisms such as the effect on home inputs and maternal employment to assess the potential for spillovers to the home environment and to assess whether the policy could induce mothers to work or affect maternal employment decisions through other indirect channels.

Table 1.12 reports the effect of the policy on various measures of parental involvement where Column (1) reports the probability of volunteering, Column (2) reports the probability of attending a parent-teacher conference, Column (3) reports the probability of attending a back to school night, Column (4) reports the probability of attending a school event, and Column (5) reports the probability of attending a parent-teacher association or parent-teacher organization meeting. I find that the school-related leave policy has positive effects on the probability of volunteering, attending a parent-teacher conference and attending a back to school night, with the effect sizes statistically largest for attending a parent-teacher conference. I do not find an effect on attending a school event, but find a negative effect of attending a PTA or PTO meeting. The differences in the effect of the policy across different types of parental involvement activities may speak to the propensity for them to occur during traditional work hours, though the negative effect on attending a PTA or PTO meeting is counter intuitive, and could possibly be coming through indirect mechanisms.

I also evaluate the effect of the policy on maternal employment and home inputs in table 1.13 to test whether the policy can induce mothers to work either by making work more attractive or through other indirect channels, and to test a hypothesis in the literature that greater parental involvement can lead to an improvement in the home environment (Wherry (2004)), as was found

Table 1.12: Potential Parental Involvement Mechanisms

	(1) Volunteer	(2) Conference	(3) Back to School Night	(4) School Event	(5) PTA/PTO Meetings
Policy	0.0062^{**}	0.0394^{***}	0.0179^{***}	0.0042	-0.0068^{**}
	(0.0030)	(0.0071)	(0.0036)	(0.0032)	(0.0029)
Observations	21750	21750	21700	21750	21750

Notes: Column (1) reports the probability of volunteering, Column (2) reports the probability of attending a parent-teacher conference, Column (3) reports the probability of attending a back to school night. Column (4) reports the probability of attending a school event, Column (5) reports the probability of attending a parent-teacher association or parent-teacher organization meeting and Column (6) reports the number of meetings at the school the parent attended. Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors clustered at the school level are reported in parentheses. The full set of controls have been suppressed for brevity. The full set of controls are child gender, mother's age, mother's age squared, mother's education status, annual household income (000's), child race, family structure, primary language spoken at home, state-level expenditure per pupil, GDP per capita, the unemployment rate, the average weekly welfare benefit, the maximum number of weeks of welfare benefits, and the average unemployment insurance claims, and year dummies. * refers to statistical significance at the 10% level, ** refers to statistical significance at the 5% level, *** refers to statistical significance at the 1% level.

in Avvisati (2013). I find evidence to suggest that the school-related leave policy matters for both employment and home inputs with a 1 hour increase in the hours of school related leave allowed off leading to a 0.006 per cent increase in the probability of employment and a 0.005 standard deviation increase in the level of home inputs, potentially due to the reasons outlined previously.

Table 1.13: Potential Alternate Mechanisms

	(1) Employment	(2) Home Inputs
Policy	0.0063**	0.0050***
	(0.0027)	(0.0010)
Observations	21750	21750
R^2		0.06

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors clustered at the school level are reported in parentheses. The full set of controls have been suppressed for brevity. The full set of controls are child gender, mother's age, mother's age squared, mother's education status, annual household income (000's), child race, family structure, primary language spoken at home, state-level expenditure per pupil, GDP per capita, the unemployment rate, the average weekly welfare benefit, the maximum number of weeks of welfare benefits, and the average unemployment insurance claims, and year dummies. * refers to statistical significance at the 10% level, ** refers to statistical significance at the 5% level, *** refers to statistical significance at the 1% level.

Heterogeneous Mechanisms

In this section, I explore whether heterogeneity in the effects of the policy on potential mechanisms can explain the lesser effects of the policy on outcomes for Hispanic individuals and the negative effects on individuals who do not speak English as the primary language at home. I present the results in tables 1.14 to 1.17 below.

I first examine heterogeneity in the effect of the policy by race on the various types of parental involvement in table 1.14. I find that the policy has a lesser effect of attending a parent-teacher conference for Hispanic students. Seemingly counter to the lesser effect of the policy on outcomes, I also find that the policy has larger effects for Hispanic students on the probability of attending a back to school night. Without further information on the signs and magnitudes of the effect of these mechanisms on outcomes, it is difficult to determine which effect outweighs the other.

Looking at the alternate mechanisms, I also find some evidence that the policy has negative effects on the probability of maternal employment for Hispanic individuals in table 1.14, however the effects are very small in magnitude.

Table 1.14: Heterogeneous Effects of the Policy on Mechanisms by Race

	(1) Volunteer	(2) Conference	(3) Back to School Night	(4) School Event	(5) PTA/PTO Meetings
Policy	0.0035	0.0615***	0.0099*	0.0076*	−0.0045
	(0.0038)	(0.0097)	(0.0053)	(0.0046)	(0.0039)
Policy*Black	−0.0140	−0.0251	0.0035	0.0034	−0.0121
	(0.0106)	(0.0180)	(0.0120)	(0.0111)	(0.0089)
Policy*Hispanic	0.0035	−0.0263***	0.0145**	−0.0022	−0.0045
	(0.0040)	(0.0100)	(0.0062)	(0.0052)	(0.0039)
Policy*Other	0.0079*	−0.0335***	0.0057	−0.0106*	−0.0011
	(0.0046)	(0.0112)	(0.0069)	(0.0057)	(0.0042)
Black	−0.3852***	0.3597**	−0.3429***	−0.4299***	0.7324***
	(0.0892)	(0.1723)	(0.0940)	(0.1048)	(0.0879)
Hispanic	−0.3251***	0.1593	−0.0432	−0.0417	0.1714**
	(0.0800)	(0.1424)	(0.0963)	(0.0935)	(0.0728)
Other	−0.4840***	0.5879***	−0.4843***	−0.3370***	0.1256
	(0.0880)	(0.1623)	(0.1041)	(0.0974)	(0.0815)
Observations	21750	21750	21700	21750	21750

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors clustered at the school level are reported in parentheses. The full set of controls have been suppressed for brevity. The full set of controls are child gender, mother's age, mother's age squared, mother's education status, annual household income (000's), child race, family structure, primary language spoken at home, state-level expenditure per pupil, GDP per capita, the unemployment rate, the average weekly welfare benefit, the maximum number of weeks of welfare benefits, and the average unemployment insurance claims, and year dummies. * refers to statistical significance at the 10% level, ** refers to statistical significance at the 5% level, *** refers to statistical significance at the 1% level.

Table 1.15: Heterogeneous Effects of the Policy on Alternate Mechanisms by Race

	(1) Employment	(2) Home Inputs
Policy	0.0111^{***}	0.0050^{***}
	(0.0043)	(0.0012)
Policy*Black	0.0061	0.0001
	(0.0115)	(0.0041)
Policy*Hispanic	-0.0112^{**}	-0.0002
	(0.0050)	(0.0015)
Policy*Other	-0.0014	0.0002
	(0.0052)	(0.0018)
Black	0.2094^{**}	-0.2716^{***}
	(0.0958)	(0.0368)
Hispanic	0.0525	-0.1464^{***}
	(0.0858)	(0.0314)
Other	0.0706	0.0239
	(0.0969)	(0.0335)
Observations	21750	21750
R^2		0.07

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors clustered at the school level are reported in parentheses. The full set of controls have been suppressed for brevity. The full set of controls are child gender, mother's age, mother's age squared, mother's education status, annual household income (000's), child race, family structure, primary language spoken at home, state-level expenditure per pupil, GDP per capita, the unemployment rate, the average weekly welfare benefit, the maximum number of weeks of welfare benefits, and the average unemployment insurance claims, and year dummies. * refers to statistical significance at the 10% level, ** refers to statistical significance at the 5% level, *** refers to statistical significance at the 1% level.

Table 1.16: Heterogeneous Effects of the Policy on Mechanisms by Primary Language Spoken at Home

	(1) Volunteer	(2) Conference	(3) Back to School Night	(4) School Event	(5) PTA/PTO Meetings
Policy	0.0021	0.0442***	0.0161***	0.0021	−0.0070**
	(0.0034)	(0.0077)	(0.0042)	(0.0038)	(0.0033)
Policy*Non-English	0.0116***	−0.0095	0.0035	0.0042	0.0006
	(0.0036)	(0.0066)	(0.0046)	(0.0040)	(0.0035)
Non-English	−0.6386***	−0.0215	−0.5723***	−0.5869***	0.4112***
	(0.0853)	(0.1286)	(0.1033)	(0.1003)	(0.0816)
Observations	21750	21750	21700	21750	21750

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors clustered at the school level are reported in parentheses. The full set of controls have been suppressed for brevity. The full set of controls are child gender, mother's age, mother's age squared, mother's education status, annual household income (000's), child race, family structure, primary language spoken at home, state-level expenditure per pupil, GDP per capita, the unemployment rate, the average weekly welfare benefit, the maximum number of weeks of welfare benefits, and the average unemployment insurance claims, and year dummies. * refers to statistical significance at the 10% level, ** refers to statistical significance at the 5% level, *** refers to statistical significance at the 1% level.

Counter to the negative effects of the policy for individuals who do not speak English as the primary language at home, I find that the policy has a positive effect on volunteering at school relative to individuals who do not speak English as the primary language spoken at home in table 1.16. I do not find any heterogeneous effects of the policy on the alternate mechanisms considered in table 1.17.

Table 1.17: Heterogeneous Effects of the Policy on Potential Alternate Mechanisms by Home Language

	(1) Employment	(2) Home Inputs
Policy	0.0074**	0.0044***
	(0.0033)	(0.0010)
Policy*Non-English	−0.0030	0.0016
	(0.0040)	(0.0014)
Non-English Home Language	−0.3094***	−0.0555
	(0.0839)	(0.0358)
Observations	21750	21750
R^2		0.07

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors clustered at the school level are reported in parentheses. The full set of controls have been suppressed for brevity. The full set of controls are child gender, mother's age, mother's age squared, mother's education status, annual household income (000's), child race, family structure, primary language spoken at home, state-level expenditure per pupil, GDP per capita, the unemployment rate, the average weekly welfare benefit, the maximum number of weeks of welfare benefits, and the average unemployment insurance claims, and year dummies. * refers to statistical significance at the 10% level, ** refers to statistical significance at the 5% level, *** refers to statistical significance at the 1% level.

I briefly discuss some of the heterogeneous effects of the policy on mechanisms along the previous dimensions considered. For the sake of brevity, I only present the results where I find evidence of heterogeneity in the effects of the policy on the mechanisms of interest.

I find limited evidence that the policy has heterogeneous effects on the various types of parental involvement by grade in table 1.18. Interestingly, whereas I do not find evidence of the policy in the baseline model, I find that the policy has positive effects on the probability of attending a school event in grade 3.

I also find limited evidence to suggest heterogeneity in the effect of the policy on mechanisms by maternal education status, with the exception of a less negative effect of the policy on attending a PTA/PTO Meetings in table 1.19.

Table 1.18: Heterogeneous Effects of the Policy on Mechanisms by Grade

	(1) Volunteer	(2) Conference	(3) Back to School Night	(4) School Event	(5) PTA/PTO Meetings
Policy	0.0071**	0.0408***	0.0147***	0.0013	−0.0047
	(0.0033)	(0.0077)	(0.0040)	(0.0034)	(0.0031)
Policy*Grade 2	−0.0005	−0.0060	0.0039	0.0028	−0.0027
	(0.0024)	(0.0057)	(0.0035)	(0.0033)	(0.0020)
Policy*Grade 3	−0.0028	0.0036	0.0077	0.0082**	−0.0045*
	(0.0025)	(0.0061)	(0.0048)	(0.0036)	(0.0023)
Grade 2	−0.2246***	−0.4432***	−0.2203***	−0.1707***	0.0199
	(0.0454)	(0.0880)	(0.0595)	(0.0631)	(0.0427)
Grade 3	−0.4193***	−0.9945***	−0.0246	−0.3498***	0.0156
	(0.1057)	(0.2019)	(0.1310)	(0.1350)	(0.1099)
Observations	21750	21750	21700	21750	21750

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors clustered at the school level are reported in parentheses. The full set of controls have been suppressed for brevity. The full set of controls are child gender, mother's age, mother's age squared, mother's education status, annual household income (000's), child race, family structure, primary language spoken at home, state-level expenditure per pupil, GDP per capita, the unemployment rate, the average weekly welfare benefit, the maximum number of weeks of welfare benefits, and the average unemployment insurance claims, and year dummies. * refers to statistical significance at the 10% level, ** refers to statistical significance at the 5% level, *** refers to statistical significance at the 1% level.

Table 1.19: Heterogeneous Effects of the Policy on Mechanisms by Education Status

	(1) Volunteer	(2) Conference	(3) Back to School Night	(4) School Event	(5) PTA/PTO Meetings
Policy	0.0061*	0.0345***	0.0199***	0.0059*	−0.0107***
	(0.0034)	(0.0078)	(0.0041)	(0.0034)	(0.0032)
Policy*College	0.0041	0.0105	−0.0070	−0.0010	0.0074**
	(0.0037)	(0.0066)	(0.0048)	(0.0045)	(0.0034)
Policy*Bachelors	−0.0032	0.0130	−0.0012	−0.0068	0.0051
	(0.0042)	(0.0083)	(0.0055)	(0.0049)	(0.0036)
Some College	0.3202***	0.2156**	0.4851***	0.4916***	−0.0216
	(0.0593)	(0.0887)	(0.0732)	(0.0661)	(0.0543)
Bachelors or Higher	0.7753***	0.6636***	0.7648***	0.9463***	0.1344**
	(0.0688)	(0.1290)	(0.0866)	(0.0922)	(0.0604)
Observations	21750	21750	21700	21750	21750

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors clustered at the school level are reported in parentheses. The full set of controls have been suppressed for brevity. The full set of controls are child gender, mother's age, mother's age squared, mother's education status, annual household income (000's), child race, family structure, primary language spoken at home, state-level expenditure per pupil, GDP per capita, the unemployment rate, the average weekly welfare benefit, the maximum number of weeks of welfare benefits, and the average unemployment insurance claims, and year dummies. * refers to statistical significance at the 10% level, ** refers to statistical significance at the 5% level, *** refers to statistical significance at the 1% level.

I find limited evidence to suggest that there is heterogeneity in the effect of the policy by household income on various forms of parental involvement in table 1.20. Specifically, I find that the policy has negative effects on the probability of attending a school event for individuals in higher income brackets.

Overall, despite finding evidence of heterogeneity in the effects of the policies on outcomes, particularly for Hispanic individuals and individuals who do not speak English as the primary language at home, I find limited evidence of heterogeneity in the effect of the policy on the various potential mechanisms captured in the dataset. It is possible that the negative effects of the policy could be operating through mechanisms not captured in the dataset, that disproportionately affect individuals who do not speak English as the primary language at home.

Table 1.20: Heterogeneous Effects of the Policy on Mechanisms by Household Income

	(1) Volunteer	(2) Conference	(3) Back to School Night	(4) School Event	(5) PTA/PTO Meetings
Policy	0.0058^{*}	0.0410^{***}	0.0164^{***}	0.0020	-0.0068^{**}
	(0.0030)	(0.0073)	(0.0036)	(0.0033)	(0.0029)
Policy*Income	-0.0054^{*}	0.0071	-0.0065	-0.0095^{**}	0.0012
	(0.0032)	(0.0070)	(0.0040)	(0.0039)	(0.0027)
Household Income	0.7058^{***}	0.2642^{**}	0.4751^{***}	0.7075^{***}	0.1783^{***}
	(0.0564)	(0.1076)	(0.0770)	(0.0808)	(0.0516)
Observations	21750	21750	21700	21750	21750

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors clustered at the school level are reported in parentheses. The full set of controls have been suppressed for brevity. The full set of controls are child gender, mother's age, mother's age squared, mother's education status, annual household income (000's), child race, family structure, primary language spoken at home, state-level expenditure per pupil, GDP per capita, the unemployment rate, the average weekly welfare benefit, the maximum number of weeks of welfare benefits, and the average unemployment insurance claims, and year dummies. * refers to statistical significance at the 10% level, ** refers to statistical significance at the 5% level, *** refers to statistical significance at the 1% level.

1.5 Conclusion

Facilitating increased contact between parents and teachers in an effort to improve outcomes has been the cornerstone of United States education policy for the past two decades. Given the centrality of parental involvement to national education policy, policy makers have expended a considerable degree of effort to design and implement policies aimed at addressing the most salient barriers to parental involvement, chief of which is an inability to get the time off of work. In response to this, 14 states have implemented a policy and a further 4 states currently have pending bills that would allow parents time off from their place of work to participate in their child's schooling. Despite the popularity of the policy, to the best of my knowledge, there is no empirical evidence of the effects of the policy, or on its associated mechanisms. By exploiting access to a rich data set with the ability to be linked to these state-level policies, I am both able to quantify the total effects of the policies and speak to some mechanisms through which the policy is likely affecting outcomes.

I find support for positive effects of the policy on math skills and limited evidence for effects on reading and non-cognitive skills. I find that the policy positively affects various dimensions of parental involvement such as volunteering, attending a parent teacher conference, and attending a back to school night. I additionally find positive effects on other inputs such as maternal employment and home inputs.

In the context of the current policy climate with fourteen states currently having the policy in place and a further four states proposing bills to introduce this policy, my research can serve as a source of information to policy makers as well as a foundation from which further analysis of the effects and mechanisms of the policy can be studied.

CHAPTER 2

THE EFFECT OF PARENTAL INVOLVEMENT ON STUDENT OUTCOMES

2.1 Introduction

Increasing the level of parental involvement in schools as a means to improving outcomes and reducing achievement gaps has been central to United States education policy over the past two decades. Recent federal education acts such as the current 2015 Every Student Succeeds Act and the preceding 2001 No Child Left Behind Act have cemented parental involvement as a national education priority by tying the receipt of federal funds to implementing parent involvement activities. Under the current act, districts in receipt of Title 1 funds are required to implement parental involvement programs, activities and procedures, and those in receipt of in excess of $500,000 are required to earmark 1% of these funds for parental involvement activities. In the year 2017, this amounted to the federal government spending an estimated $133,000,000 on parental involvement activities.[1] Using a large nationally representative survey, this paper recovers the causal effect of parental involvement on child outcomes by addressing the non-random nature of parental involvement and accounting for the inter-dependence between parental involvement and other input decisions relevant to child skill production. This paper also studies the effects of existing state-level policies that allow parents time off from their place of work to participate in their child's schooling.

Thus far the literature has struggled to identify the causal effect of parental involvement due to issues of selection and the omission of relevant variables to child skill production and parental involvement decisions. The former stems from the likely presence of unobserved inputs that have the potential to influence both the parental involvement and child skill decision leading to a biased

[1]The figure was computed using Title 1 federal allocations by district provided by the U.S. Department of Education. The figure assumes that actual allocations were as reported in the data and that there was an 100% compliance rate.

estimate of the effect of parental involvement on child outcomes. For instance, parents of inherently higher (unobserved) ability children may both have a higher level of parental involvement and have higher skilled children leading to an upward bias in the effect of parental involvement. Conversely, parents may compensate for having an inherently low (unobserved) ability child by having a high level of parental involvement leading to a downward bias in the effect of parental involvement. Similarly, failure to account for the effect of other related inputs may lead to an over or understating of the effect of parental involvement. For instance, an increase in parental involvement may lead to a reduction in other competing productive uses of the parents' time such as employment or home input decisions with ambiguous effects on child skill development. By modeling parental involvement, maternal employment, fertility and home inputs as a set of interrelated parental input decisions and using econometric techniques to correct for the non-random nature of parental involvement and other related inputs, this paper is able to recover the causal effect of parental involvement.

Policies designed to increase parental involvement can affect other inputs directly, as well as indirectly through the effect of changing parental involvement on other inputs with ambiguous total effects on child skill. For instance, the existing state-level policies that allow parents time off from work to participate in their child's schooling may lead to an increase in parental involvement, but it may also directly lead to increases in maternal employment. Additionally, increasing the level of parental involvement may lead to reductions in home inputs and employment due to parental time constraints. Quantifying the total effect of these policies requires accounting for both these direct and indirect channels. By specifying and estimating a sufficiently rich model that (1) captures the inter-dependence of inputs, (2) models the dependence of these inputs on policies, and (3) recovers causal effects of these inputs on child skill, this paper is able to evaluate the total effects of policies designed to reduce the barriers parents face to involvement.

I develop my empirical specification from a theoretical model similar to the Hanushek (1986) and Becker and Tomes (1979) models where parents value consumption, leisure and their child's human capital. I extend the previous models to consider parental involvement as an investment in human capital and non-cognitive skills and allow for parents to derive utility from their child's non-cognitive skills in addition to their child's human capital. I present the model from the standpoint of a forward-looking utility maximizing household with the mother as the decision-making agent making choices over parental involvement, home inputs, fertility and employment decisions as inputs into child skill formation each period. I include home inputs, fertility and employment decisions as these have the potential to both affect and be affected by parental involvement decisions and have been shown to be relevant for child skill formation (Del Boca (2014); Bernal (2008)). By treating parental inputs as sequential per period decisions made simultaneously within each period, I am able to capture both the contemporaneous trade-offs parents face in terms of competing productive uses of their time as well as the dynamic effects of parental input decisions. From the theoretical model, I derive approximations to the parental involvement and other related input decisions as a linear function of all information available to the mother at the time of her making her input decisions.

In my empirical specification, I control for several sources of unobserved heterogeneity that can potentially bias results including mother/child permanent unobserved heterogeneity, such as unobserved child ability, mother/child time-varying unobserved heterogeneity, such as health shocks to the child or mother, and show relative robustness to the inclusion of school-level permanent unobserved heterogeneity. I account for these forms of heterogeneity by using a random effects specification that categorizes mother/child permanent unobserved heterogeneity and mother/child time-varying unobserved heterogeneity into a discrete number of family types and shocks, respectively. I include these terms directly in the input decisions and skill equations and allow for correlation in the error terms across equations and time. The direct inclusion of these terms resolves the omitted variable bias problem stemming from the omission of these unobserved inputs that likely both affect input decisions and skill formation. In addition to including these terms, I use exclusion restrictions derived from the theoretical model to identify the causal effect of parental involvement. The exclusion restrictions are assumed to be correlated with input decisions but conditional on these input decisions do not directly affect skill formation, making them valid exogenous shifters of input decisions. In generating my exclusion restrictions, I exploit the ability to link the dataset to state-level variables and rely on a novel source of identification by exploiting plausibly exogenous variation in an employment-based law that allows parents time off from their place of work to participate in their child's schooling, in addition to labor market characteristics, and state welfare, child-care, and taxation policies.

I find evidence of a positive and statistically significant effect of parental involvement, as measured by volunteering at school, on math, reading, and non-cognitive skills of 0.04, 0.04, and 0.05 standard deviations, respectively. To get an idea of these magnitudes, the effect sizes are comparable to 19%, 17%, and 64%, respectively, of the direct effect of a mother having a bachelor's degree or higher. The effect sizes are of the same sign but larger in magnitude when compared with the baseline OLS model. By contrast, when analyzing parent-teacher conferences as the measure of parental involvement, I find stark differences in math and reading skills between the baseline OLS results and the results from the model that corrects for the endogeneity of parental involvement and other input decisions. I find a negative and statistically significant effect of attending a parent-teacher conference on reading skills in the baseline OLS model of 0.05 standard deviations, however this effect becomes insignificant when the endogeneity of the parent-teacher conference decision is accounted for. Similarly, I find an insignificant effect of attending parent-teacher conferences on math skills in the baseline OLS model compared with a positive and statistically significant effect of 0.04 standard deviations in the model correcting for selection, though only at the 10% level. The results are consistent with a negative selection mechanism whereby parents of lower ability children are more likely to attend parent-teacher conferences, leading to a downward bias in OLS estimates. Conversely, I find negative effects of attending a parent-teacher conference on non-cognitive skills for both specifications of 0.07 standard deviations in the baseline OLS model and 0.06 standard deviations in the model that corrects for the endogeneity of the parent-teacher conference decision. I additionally find evidence of a dynamic positive effect of lagged volunteering on contemporaneous home inputs which subsequently affect child skill.

Using my estimated empirical model, I simulate the effects of a policy aimed at reducing the primary impediment to parental involvement, informed by the most frequent reason parents report have made it harder to participate in their child's schooling as captured by my dataset. Because parents report "cannot get the time off of work" as the primary reason hindering their participation, I focus on existing state-level policies that allow parents time off from their place of work to participate in their child's schooling, providing the first evaluation of this policy. Quantifying the effects of the policy is a timely and relevant exercise given that 14 states currently have the policy implemented and a further four currently have pending bills.[2] I find that allowing parents 40 hours off of work in leads to increases in non-cognitive skills over the life cycle of the child primarily through increasing the level of volunteering.

I make several important contributions to several strands of the literature. First, I contribute to the literature on the effects of parental involvement by dealing with endogeneity due to selection on unobservables and accounting for the effect of other related input decisions allowing for consistent estimates of the effect of parental involvement on child outcomes to be recovered. My research complements prior papers that have implemented strategies to deal with the endogeneity of parental involvement such as Avvisati (2013) who exploit a randomized experiment in French middle schools and De Fraja and Zanchi (2010) who consider the effect of a construct similar to parental involvement on the probability of the child obtaining a UK GCSE qualification at age 16-17 using a three-stage least squares approach. My research also builds upon prior work in the education literature that has documented associations between parental involvement and child outcomes with estimates ranging from positive (Domina (2005); Jeynes (2005); Stewart (2008); Shumow and Miller (2001)), to negative (Izzo (1999)), to no effects (Domina (2005); Bobbett (1995)).

Second, I contribute to the literature by providing, to the best of my knowledge, the first evaluation of the effect of policies geared at facilitating parental involvement on child outcomes. Efforts to facilitate greater contact between parents and schools have been made at the national, state, district and school level, yet there is no evidence as to whether these policies have their intended effects. By exploiting the ability to link my dataset to state-level policies in combination with my empirical strategies, I am able to quantify the effects of policies aimed at facilitating greater

[2]The states that currently have school-related leave laws are Arkansas, California, Colorado, Hawaii, Illinois, Massachusetts, Minnesota, Nevada, New Mexico, North Carolina, Rhode Island, Texas, Vermont, and Virginia in addition to District of Columbia. The states that currently have pending bills are New York, New Jersey, Connecticut, and Michigan.

parent-school contact highlighting increases in parental involvement as the primary mechanism.

Third, I contribute to the economics literature that has largely analyzed the effect of home inputs on child cognitive and non-cognitive skill development, by demonstrating the effect of parental involvement on home inputs. For instance, Bernal (2008), Del Boca (2014), Fiorini and Keane (2014), Del Bono (2016), Cunha and Heckman (2008), and Wolpin and Todd (2007) all demonstrate the importance of various measures or proxies of home inputs to child skill development. I complement the existing literature by considering an alternate form of parental inputs that has been positively associated with child skill and an increase in home inputs, and is the subject of recent national education policy. Prior papers have alluded to the changing nature of the child skill production function when the child begins formal schooling, as the primary learning environment shifts from the home to the school and other agents become relevant to child skill formation (Del Boca (2014); Bernal (2008)), but have not considered the effect of other parental inputs that are relevant to this stage of the child's life. My research extends the literature by demonstrating the role parental involvement plays when the child comes of school age in addition to showing how parental involvement can affect home inputs which have traditionally been the focus of study in the literature.

The rest of the paper proceeds as follows, Section 2.2 discusses the data to be used in the estimation and why it is well-suited for this analysis. Section 2.3 describes the theoretical model that serves as a basis for the empirical section. Section 2.4 gives the empirical specification, discussing estimation and identification. Section 2.5 gives results. Section 2.6 discusses the effects of policy simulations and Section 2.7 concludes.

2.2 Data

The dataset used for this analysis is the Early Childhood Longitudinal Study, Kindergarten Class (ECLS-K), a nationally representative sample of kindergarteners in the United States who began kindergarten in the fall of 2010. The ECLS-K is a longitudinal survey of children, including detailed information on their parents, schools and teachers. The survey collects information on home and school inputs, in addition to cognitive and non-cognitive measures for children, making the dataset well-suited to this analysis. The restricted use ECLS-K dataset contains information on the state of residence of the child, allowing the dataset to be merged with other geocoded datasets on welfare benefits, employment legislation, labor market conditions, tax rates, and child care subsidies which are useful for identifying the parameters of interest and evaluating the effects of policy. There are currently four main waves of data: the fall (2010) and spring (2011) of kindergarten, the spring of grade 1 (2012),[3] the spring of grade 2 (2013), and the spring of grade 3 (2014) with the spring of grades 4 (2015) and 5 (2016) forthcoming. The initial sample in the fall of kindergarten consisted of approximately 18200 children, however there was attrition in the survey with each additional wave (See Appendix Table F.2.1).

The sample I use for this analysis makes use of the spring of kindergarten,[4] the spring of grade 1, the spring of grade 2, and the spring of grade 3. In constructing my estimation sample, I drop individuals if they are missing data on outcome variables and key input variables such as math, reading and non-cognitive scores in addition to data on home inputs, the number of other children, parental involvement measures, and maternal employment decisions. Since part of my robustness checks rely on variation within a school, I drop observations where I only observe one individual per school.[5] For individuals who are missing information on exogenous characteristics, I include a dummy variable to indicate the presence of missing data for continuous variables, and include a missing data category for categorical variables. I drop individuals who are not observed in the fall of kindergarten, since key variables of interest are only asked in the fall. I also drop individuals who are retained in any grade since I do not model the retention decision. Similarly, since I do not model the decision to change schools each period, I retain individuals until they change schools and consider them as having attrited after they change schools.[6] I compare key variables from the original and estimation sample in Appendix Tables F.2.2 to F.2.4 to indicate how the two samples

[3]A small sub-sample of the children were surveyed in the fall of grade 1 and the fall of grade 2.

[4]Information from the spring of kindergarten is used for initial information about the child. I do not use the fall of kindergarten as the initial period as key variables of interest were not collected during the fall period.

[5]In order to retain a reasonable sample size, I impute non-cognitive scores for individuals who have math and reading scores but are missing non-cognitive scores using predicted values from linear regressions.

[6]The proportion of children changing schools over each wave are as follows: Wave 1 to Wave 2: 1.74 %, Wave 2 to Wave 3: 8.85%, Wave 3 to Wave 4: 14.39%, Wave 4 to Wave 5: 21.40%

compare after the restrictions are imposed. I standardize the measure of home inputs and the cognitive and non-cognitive scores for ease of interpretation. Cognitive scores are standardized relative to kindergarten levels as the scores are constructed to be horizontally comparable across grades. I measure parental involvement using two binary variables: whether the parent volunteers at school or not and whether the parent attended a parent-teacher conference or not, both as reported by the parent, aimed at capturing different dimensions of parental involvement in schools. One concern is that parents may be constrained by the availability of opportunities to volunteer, however, in figure G.2.1 in the Appendix, I provide suggestive evidence that this is unlikely to hold by presenting parents' reports on how satisfied they are with being made aware of opportunities to volunteer. As can be seen from the figure, relatively few parents report dissatisfaction with being made aware of opportunities to volunteer. Similarly, I argue that parents are unlikely to be constrained by opportunities to attend parent-teacher conferences as reflected by the high degree of parents that report attending parent-teacher conferences (See table F.2.4). Nevertheless, I present supporting evidence that they are unlikely to be constrained by opportunities by showing how often the schools hold parent-teacher conferences as reported by the school in figure G.2.2 in the Appendix.

I define home inputs as activities parents partake in with their children outside the realm of the school.[7] The construct of home inputs is the simple average of four variables: the frequency the child reads books, whether the child participates in extra-curricular activities, whether the number of hours of TV watched on a weekday is above or below the sample median, and how often the family eats dinner together.[8] The average of the standardized home input index and summary

[7]One concern is that parental inputs at home and parental involvement at school may be both proxying for underlying latent parenting quality, however, I provide theoretical and empirical evidence that suggests the two are distinct constructs. Firstly, parental involvement at school is an established concept in the education literature, and is treated as a distinct concept from home inputs. Secondly, the theoretical existence of these as two separate dimensions of parental inputs is validated statistically as suggested by the presence of two distinct factors when all variables are put together, one that loads more on variables used in the construction of home inputs and one that loads more on variables used in the parental involvement measure. Lastly, the correlation between volunteering at school and home inputs is 0.13, 0.15, 0.14, and 0.16 across the four waves, and the correlation between attending a parent-teacher conference and home inputs are 0.04, 0.07, 0.06, and 0.06, a relatively lower degree of correlation than one would expect if the two measures were capturing the same underlying dimension of parenting skill.

[8]I constrained my construct to variables that were available across all four waves for consistency in interpretation of the construct.

statistics of the variables used to construct the index are presented in Appendix table F.2.4.

Non-cognitive skills are extracted as a latent factor from the following teacher-reported measures: Approaches to learning, Self-control, Inter-personal skills, Externalizing and Internalizing problem behaviours, Inhibitory Control and Attentional Focus. I aggregate these measures into a single index using polychoric analysis for convenience and to reduce the number of parameters to be estimated. I outline the procedure used to aggregate the non-cognitive scores in section A.2.1 of the appendix. The factor loadings associated with these variables are shown in Appendix Table F.2.5. Approaches to Learning and Self-control are the variables that load most highly onto the non-cognitive factor across all four waves.

Cognitive skills are measured by Item Response Theory (IRT) math and reading scores based on standardized cognitive tests collected as part of the ECLS-K survey. I discuss the advantages of using IRT test scores in section A.2.1 of the Appendix.

2.3 Theoretical Model

In this section I describe a model of human capital formation that highlights some direct and indirect ways in which parental involvement can affect child outcomes based on mechanisms highlighted in the economics and education literatures. The model developed here is based on the Hanushek (1986) and Becker and Tomes (1979) models in which parents value consumption, leisure and their child's human capital and face trade-offs in deciding between investments in their child and their own consumption. I highlight some key characteristics of the model below. First, I allow parental involvement to be an additional form of parental investment once the child enters formal schooling, complementing previous work that has focused on a uni-dimensional measure of parental inputs. Second, by modeling the parents' other time commitments such as employment, home input, and fertility decisions, I capture the trade-offs parents face when deciding their level of involvement. Third, by modeling the input decisions as per-period sequential decisions, I account for the dynamic effects of input decisions and the subsequent effects on child skill formation. Last, I allow parents to derive utility from their child's non-cognitive skills extending the previous models that focused exclusively on cognitive skills. In the theoretical model, I treat the household as a unitary decision maker. Specifically, I model decisions from the perspective of the mother and abstract away from issues of intra-household bargaining.[9]

2.3.1 Human Capital and Non-Cognitive Skill Production Function

I first specify a model of child skill development where i refers to the child, s refers to the school and t refers to the time. I assume that child i in school s at time 0 is born with an initial human capital endowment A^c_{is0}, which is measured by the child's performance on math and reading cognitive tests taken in the spring of kindergarten. Similarly, I assume the child's initial non-cognitive skill endowment, A^n_{is0}, is the child's non-cognitive skill based on teacher reports in the spring of kindergarten. Each period t, corresponding to a year, the child's human capital and non-cognitive skills evolve according to production functions specified below. I model the production functions as value-added production functions where the child's stock of skills of type k at the end of the period, A^k_{ist}, is assumed to be a function of the child's prior level of cognitive and non-cognitive skills, the inputs determined by the parents, and family socio-economic and demographic characteristics. In my empirical specifications, I do not include both lagged math and reading skills in the same specification due to the high degree of correlation between these two variables. In this specification, the prior level of skill is assumed to be a sufficient statistic for the child's initial skill endowment, A^k_{is0}, as well as all prior inputs.[10]

In order to conserve on notation, I denote my two measures of parental involvement, volunteering at school, I^1_{ist}, and attending a parent-teacher conference, I^2_{ist}, by the vector $I_{ist} = (I^1_{ist}, I^2_{ist})$ and jointly refer to them as parental involvement in school. In addition to parent involvement in school, I_{ist}, I include other relevant jointly determined inputs such as home inputs, H_{ist}, the maternal employment decision, E_{ist}, and the number of other children in the household, K_{ist}. Home inputs capture important dimensions of the quality of the home environment and the mother's

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[9]The assumption that the mother makes the decisions is not an unreasonable one. In the previous version of this survey, the question was asked as to who participated in activities at the child's school, 15.6% of respondents reported that mothers attended PTA meetings compared with 1.6% that reported fathers and 4.6% reported both parents. The comparable figures for attending a back to school night were 32.7%, 5.3% and 22.2%, respectively. The comparable figures for attending a parent-teacher conference were 19.1%, 2.5%, and 8.4%, respectively. The comparable figures for attending a school event were 16.0%, 2.4%, 25.4%, respectively. The comparable figures for volunteering are 20.0%, 1.6%, and 5.3%.

[10]This result can be derived by recursive substitution as per Wolpin and Todd (2003)

other time commitments, whereas maternal employment and the number of siblings in the household capture dimensions of the mother's other time commitments. In addition to inputs, I include family socio-economic and demographic characteristics of the child, parents, and household denoted by the vector X_{ist}. The vector X_{ist} includes household income, the mother's age and age squared, family structure, the primary language spoken at home, the child's gender and race, and the mother's education status. The error term in the production function equation for skill k comprises time-invariant unobserved characteristics of the child/mother, μ_{is}^k, time varying unobserved heterogeneity of the child/mother, ν_{ist}^k, as well as an idiosyncratic error term capturing idiosyncratic shocks and measurement error ϵ_{ist}^k.

The cognitive production function for child i in school s at time t can be written as:

$$A_{ist}^c = \gamma_0^c A_{ist-1}^c + \gamma_1^c A_{ist-1}^n + \gamma_2^c I_{ist} + \gamma_3^c H_{ist} + \gamma_4^c E_{ist} + \gamma_5^c K_{ist} + \gamma_6^c X_{ist} + \mu_{is}^c + \nu_{ist}^c + \epsilon_{ist}^c \quad (2.1)$$

whereas the non-cognitive production function for child i in school s at time t may be written as:

$$A_{ist}^n = \gamma_0^n A_{ist-1}^c + \gamma_1^n A_{ist-1}^n + \gamma_2^n I_{ist} + \gamma_3^n H_{ist} + \gamma_4^n E_{ist} + \gamma_5^n K_{ist} + \gamma_6^n X_{ist} + \mu_{is}^n + \nu_{ist}^n + \epsilon_{ist}^n \quad (2.2)$$

2.3.2 Timing

The model begins when the child first enters kindergarten and ends when the child completes grade 3. The household makes decisions in the spring of grade 1 (t=1), the spring of grade 2 (t=2), and the spring of grade 3 (t=3), taking the spring of kindergarten (t=0) as the initial period. The parent comes into the period observing past realizations of skills, consumption, leisure, involvement, home input, fertility and employment, and her current policy and labour market environment. Given the information available to her and her preferences and constraints, the parent then makes consumption, c_{ist}, leisure, l_{ist}, employment, E_{ist}, fertility, K_{ist}, specifically whether to keep the number of siblings the same $(k = 1)$, increase the number of siblings, $(k = 2)$, or decrease the number of siblings, $(k = 3)$, home input, H_{ist}, and involvement decisions, I_{ist}. I denote the vector of the mother's input decisions by $d_{ist} = (E_{ist}, I_{ist}, H_{ist}, K_{ist})$.

2.3.3 Per-period utility and constraints

Consistent with the Becker and Tomes (1979) model, I assume the mother derives utility from her consumption, c_{ist}, leisure, l_{ist}, and her child's vector of human capital and non-cognitive skills, A_{ist}. I also assume the mother faces utility costs associated with her input decisions at time t, d_{ist}. I allow preference and cost parameters, captured by the vector α_{ist}, to depend on observable characteristics of the mother/child, X_{ist}, the mother's input decisions in the prior period d_{ist-1}, permanent unobservable characteristics of the mother/child, μ_{is}, and time-varying unobserved characteristics of the mother/child, ν_{ist}. The inclusion of observable characteristics as cost and utility shifters allows for differing preference for consumption, leisure, and child skill along dimensions such as race, income, family structure, and maternal education status, and differing costs of inputs along these same dimensions. Similarly, the inclusion of unobserved characteristics as cost and utility shifters allow for differing preference for consumption, leisure, and child skill, and differing utility costs along dimensions unobserved to the researcher. The inclusion of lagged decisions as cost and utility shifters allows for the utility or disutility associated with the input decisions to depend on whether and to what extent the mother has engaged in them previously. The per period utility function can be specified as follows:

$$U_{ist} = f(c_{ist}, l_{ist}, A^c_{ist}, A^n_{ist}, I_{ist}, H_{ist}, K_{ist}, E_{ist}; \alpha_{ist}) \tag{2.3}$$

where $\alpha_{ist} = g(X_{ist}, d_{ist-1}, \mu_{ist}, \nu_{ist})$

Each period, the mother maximizes the present value of her expected utility subject to budget and time constraints in addition to the child's skill production functions given in equations 1.1 and 1.2. Normalizing the mother's time endowment to 1, her per period time constraint can be specified as follows:

$$1 = l_{ist} + h_{ist} + I_{ist} + H_{ist} \tag{2.4}$$

where l_{ist} is the mother's leisure time, h_{ist} is the hours of work of the mother, I_{ist} is time devoted to parental involvement at school, and H_{ist} is time devoted to home inputs. Normalizing the price of the consumption good to 1, the budget constraint is given by:

$$c_{ist} + n_{ist}(X_{ist}, K_{ist}, J_{ist}) = w_{ist}h_{ist} + O_{ist} + B_{ist}(K_{ist}, X_{ist}, R_{ist}) \tag{2.5}$$

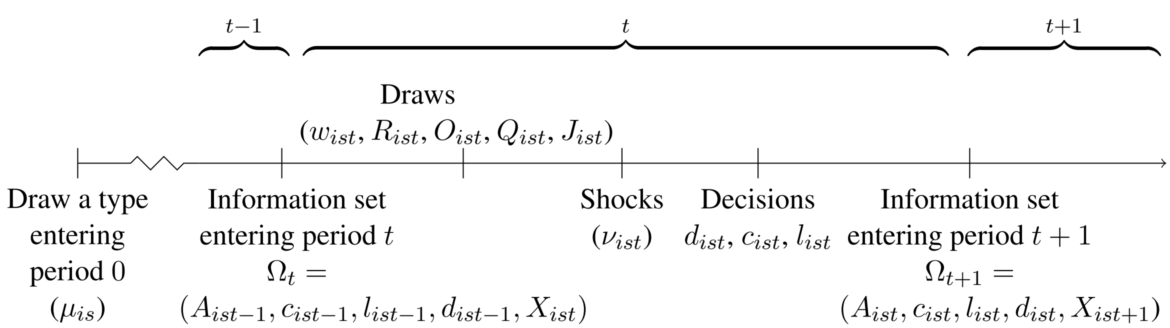
where c_{ist} is aggregate consumption, n_{ist} is expenditure on child care that is dependent on the number of children, K_{ist}, income and family structure captured in X_{ist}, and state availability of child care and state policies on child care subsidies, J_{ist}, w_{ist} is the wage rate of the mother, h_{ist} are the hours of work for the mother. O_{ist} represents other sources of income such as the mother's partner's income, if present, child support payments and gifts. B_{ist} represents other transfers received by the household such as welfare transfers or tax credits that are dependent on characteristics of the household, such as the number of children, K_{ist}, income and family structure captured in X_{ist}, and state policies on taxation and welfare, R_{ist}. The mother's wage if she works and the latent wage offer if she does not work is assumed to be drawn from a distribution which depends on state local labour market conditions, L_{ist}, the mother's prior employment, E_{ist-1}, as well as observed characteristics such as the mother's age, race, education status, and permanent unobserved characteristics of the mother, X_{ist} and μ^w_{is}, respectively according to:

$$w_{ist} \sim F(L_{ist}, X_{ist}, E_{ist-1}, \mu^w_{is}) \tag{2.6}$$

2.3.4 Dynamic Problem

At the beginning of period 0, the mother/child draws a permanent type, μ_{is}, that affects maternal preferences, the child skills technology, and wage offers. The permanent type captures groups of mothers/children that differ in similar ways due to omitted characteristics and or inputs not observed by the researcher. The mother enters each period observing her child's current stock of skill at the end of period $t-1$, A_{ist-1}, her past consumption, leisure, employment, home input, involvement, and fertility decisions, c_{ist-1}, l_{ist-1}, d_{ist-1}, her current observable characteristics in addition to her permanent type. After observing her state space, the wage offer, w_{ist}, including local labour market conditions, L_{ist}, child care availability and subsidy rules J_{ist}, social welfare and tax rules R_{ist}, other sources of income O_{ist}, and the general policy environment Q_{ist}, are realised. Subsequent to this, the time-varying shock, ν_{ist} occurs. The mother then makes her subsequent consumption, leisure, employment, fertility, home input, and involvement decisions, and the child skills and history of input decisions are updated forming the state space for the beginning of the next period. Defining $\Omega_t = (A_{ist-1}, c_{ist-1}, l_{ist-1}, d_{ist-1}, X_{ist})$ as the mother's state space at time t, the mother chooses an alternative vector $(c_{ist}, l_{ist}, d_{ist})$ from the set of possible alternatives to maximise her current utility plus the discounted expected value of her future utility where the expectation is taken over the future wage offers, other sources of income, labour market conditions, welfare and taxation rules, availability of child care and state child care subsidy rules, the general policy environment, shocks to child skill, and to utility. The decision making process within a period can be summarized in the figure below:

Figure 2.1: Timing of Decisions, Information Set and Stochastic Realizations



2.3.5 Approximation to the solution of the parent's problem

Since the mother is a forward-looking individual and since choices today affect future maternal utility directly through the evolution of child skill, and indirectly through their effects on contemporaneous input decisions, the mother's choice is inherently dynamic. Each period t the mother makes decisions d_{ist}, c_{ist}, and l_{ist} that maximize the present discounted value of her expected lifetime utility consisting of the current utility plus the discounted maximised expected future utility. The terminal value function $V_{T+1}(\Omega_{isT+1}|w_{isT+1}, R_{isT+1}, O_{isT+1}, Q_{isT+1}, J_{isT+1})$ is the discounted expected continuation utility of the state variables and exogenous factors at time $T+1$.

In period t, the mother's dynamic problem is:

$$\begin{aligned} V_t(\Omega_{ist}|w_{ist}, R_{ist}, Q_{ist}, O_{ist}, J_{ist}) = & \max_{d_{ist}, c_{ist}, l_{ist}} U(c_{ist}, l_{ist}, A_{ist}, d_{ist}, d_{ist-1}, X_{ist}, \mu_{is}, \nu_{ist}) \\ & + \beta \mathbb{E}_{ist}\big[V_{t+1}(\Omega_{ist+1}|w_{ist+1}, R_{ist+1}, O_{ist+1}, Q_{ist+1}, J_{ist+1})\big] \end{aligned} \tag{2.7}$$

subject to the skill production functions and the budget and time constraints.

In order to solve the full model and recover the functional forms of the demand functions, the functional forms of the utility and production functions, the distribution of the wage variable, and the continuation value function, the evolution of the mother's beliefs must be specified. The value function would then need to be computed at each period over many combinations of the state space. Given that the state space includes several continuously distributed variables, it would be computationally intractable to compute the value function at each possible value. Approximations to the decision rules sidesteps these computational issues whilst still capturing important features of the model.[11] For instance by approximating general forms of the input demand functions, I am still able to capture the dynamics of input decisions without having to solve the model fully,

[11] Two papers in the literature have employed fully structural approaches when analyzing the effect of parental inputs on child cognitive development. Bernal (2008) assumes a cumulative production function, avoiding the problem of having lagged skill entering the state space. Additionally, her control variables are child care use and employment status which are inherently discrete. Del Boca (2014) also sidestep the issue of child skill in the state space by placing restrictive functional form assumptions on the child skill production function that result in decision rules that have the undesirable feature of being independent of current child skill. This would for instance negate feedback effects whereby parents use past realization of skills to inform their current input deicions.

which would entail making potentially restrictive assumptions on the form of the utility function and what the mother knows about the production function for child human capital, the wage offer, state welfare and taxation policies, child care availability and subsidies, and welfare rules. The approximation also allows the number of children to enter the model in a flexible way by affecting all input decisions and child skill formation without having to specify maternal preferences for the skill distribution among her children which is problematic here as human capital development measures are only present for the focal child.

I estimate general forms of the demand functions by expressing each input decision as a general function of the state space and information acquired during the period prior to the mother making her decision. Since all decisions are made simultaneously with the same information available to the mother, each input decision is a function of the same variables. I use a linear approximation for the decision rules, expressing them as a function of the state space, Ω_{ist}, the policy, welfare and taxation rules, other sources of income, chid care rules and availability, and the labour market environment, denoted by the vector $Z_{ist} = (L_{ist}, R_{ist}, O_{ist}, Q_{ist}, J_{ist})$, permanent unobserved heterogeneity, μ_{is}, time-varying shocks, ν_{ist}, and idiosyncratic errors, ϵ_{ist}.

2.4 Empirical Framework

The primary interest of this study is the direct effect of parental involvement at school on child cognitive and non-cognitive skills captured by γ_2^c and γ_2^n as shown in equations 1.1 and 1.2. Of additional interest is the potential dynamic effect of parental involvement on home input decisions that has been discussed in the literature (Wherry (2004)) but never shown empirically. Estimation of the main parameters of interest, γ_2^c and γ_2^n by OLS would likely lead to biased coefficients due to the endogeneity of the parental involvement decision stemming from the likely presence of omitted unobserved inputs and reverse causality. Similar issues of omitted unobserved inputs prevents ascribing a causal interpretation to the coefficients on home inputs, employment and fertility decisions. Lastly, the coefficients on the lagged skills are likely biased due to the presence of permanent unobserved heterogeneity, which by definition affects skills in all periods, and introduces correlation between lagged skills and the composite error term.

For instance, the coefficients on parental involvement in the child skill equations will be biased upwards if higher skilled parents are both more likely to have higher skilled children and to have a higher level of parental involvement due to the presence of unobserved inputs at the mother/child level. Alternately, the coefficient on parental involvement is likely biased downward if there is an issue of reverse causality where parents increase their level of involvement in their child's schooling subsequent to their child doing poorly or if parents engage in compensatory behaviour whereby parents of inherently lower ability children or children who have experienced negative shocks have a higher level of participation in their child's schooling. Ex ante, it is difficult to determine the direction of the bias due to competing hypotheses, rendering it largely an empirical question. In the section that follows, I discuss the econometric method I use to address these forms of bias.

2.4.1 Full Information Maximum Likelihood

The full-information maximum likelihood (FIML) method estimates the approximations to the decision rules jointly with the child skill production functions as a system of equations allowing for correlation in the error terms across equations with the explicit inclusion of permanent and time-varying unobserved heterogeneity in the parental input and child skill equations and uses exclusion restrictions generated by the theoretical model to identify parameters of interest. By directly including the unobserved heterogeneity terms in the input decisions, the method resolves the problem of selection due to omitted variables stemming from a correlation between parental inputs and unobserved heterogeneity present in the error term of the child skill production function. Since the approximations to the parents' decision rules depend on the previous input choices made, the method allows for both the direct and indirect effect of input decisions to be quantified through the dynamic evolution of input decisions and skill formation.[12]

[12]This would not have been possible in a linear instrumental variable framework as the first-stages are estimated purely as a function of exogenous variables whereas the estimation strategy used here can accommodate lagged endogenous variables.

Unobserved Types

In order to account for the possibility that there are unobserved mother/child characteristics that can both influence parental input decisions as well as child skill formation, I employ the discrete factor random effects methodology (Heckman and Singer (1984); Mroz and Guilkey (1992); Mroz (1999)) and assume that there are a continuum of family types which are categorized into m discrete types, one of which the mother draws in period 0 as shown in in figure 2.1. Additionally, I approximate the distribution of time-varying shocks by again assuming a continuum that can be categorized into q discrete types which the mother draws each period, also shown in figure 2.1. Since the model includes a constant, I require a normalization in order to recover the mass points and probability weights. I normalize the first mass point to be equal to 0, and since the sum of the weights of each type must equal 1, I estimate $(m-1)$ and $(q-1)$ probability weights for permanent and time-varying unobserved heterogeneity, respectively. The unobserved heterogeneity parameters: μ_m and ν_{qt} and their corresponding probability weights η_m, and ω_q are estimated along with the parameter vector by full information maximum likelihood. Instead of making the usual distribution assumption of multi-variate normality of the unobserved heterogeneity parameters, I do not impose a distributional assumption and instead use a discrete factor random effects specification which estimates the mass points (types) and the probability of each type using a step function. The decision not to impose normality on the unobserved heterogeneity parameters is a deliberate one as using Monte Carlo Simulations, Mroz (1999) showed that the method employed here has been shown to perform as well as maximum likelihood estimators in terms of precision and bias when the true model is jointly normal and normality is assumed. Additionally, the method here has been shown to be more robust to violations of the normality assumption. I use a non-linear specification for unobserved heterogeneity, where mass points are estimated for each interval along with a common set of probabilities.

Attrition and Initial Conditions

Individuals may attrit from the sample naturally as well as if they change schools during the period, since I do not model the decision to change schools. I account for this potential non-random attrition by modeling attrition as a function of the outcomes and behaviours observed in the period prior to individuals attriting from the sample, exclusion restrictions, as well as observable characteristics and permanent and time-varying unobserved heterogeneity. I estimate the attrition equation jointly with the other outcome equations where $M_{ist+1} = 1$ if an individual is not present in period $t + 1$.

Since input choices and skills formation are dynamic and since I do not observe prior inputs or skills in the initial period, and by construction, mother/child unobserved heterogeneity affects all skills, input and labour force participation decisions in all periods, I need to specify an initial conditions equation for all maternal decisions as well as for the child's cognitive and non-cognitive production functions to recover the correct distribution of the unobserved heterogeneity and deal with the presence of lagged endogenous input and skill variables in the input decisions and skills production functions. Here, the initial conditions equations are estimated in reduced form and are identified using variables that affect initial input and skills but conditional on these, do not have an independent effect on subsequent inputs and skills. For my exclusion restrictions, denoted by the vector Z_{is0}, I use the child's birth weight, the child's birth order, the number of older siblings, whether the mother was married at the time of birth, the mother's age at first birth and the mother's age at first birth squared. I present summary statistics of these variables in Appendix Table F.2.6. I additionally include exogenous characteristics such as the race and sex of the child and the mother's education level.[13]

System of Equations

2.4.2 Identification

As noted before, the child skill outcomes and the parental input decisions depend on endogenous explanatory variables hence it is important to discuss whether the coefficients of interest are identified, the sources of identification, and the threats to identification. First, as mentioned previously, direct inclusion of the unobserved heterogeneity terms in the input decisions and skill

[13] The initial condition for the maternal fertility decision is the number of siblings at period 1. Subsequent per period decisions are estimated as a multinomial logit model where $k = 1$ refers to keeping the number of siblings the same, $k = 2$ refers to decreasing the number of siblings and $k = 3$ refers to increasing the number of siblings.

production functions resolves the problem of selection stemming from the omission of these variables in these equations. Similarly, the specification of initial conditions equations helps to assist in the identification of the parameters of lagged endogenous variables. Second, the theoretical model in Section 2.3 implies natural exclusion restrictions that I use to help identify the parameters of interest. For instance, child care subsidies affect input decisions through affecting the budget constraint of the household, but do not directly affect child skill formation and are assumed to be uncorrelated with the error term in the child skill equations. Additionally, state welfare and taxation rules, other sources of income, as well as transfers and credits affect the budget constraint of the mother and thus her input decisions but do not directly affect child skill formation. Third, due to the dynamic nature of input decisions, current input decisions depend on prior input decisions and though recursive substitution, the entire history of prior inputs, and by extension the entire history of exogenous variables. As such, the entire history of exogenous variables serve as exclusion restrictions since they will affect the trajectory of maternal behavioural choices and thus contemporaneous maternal inputs due to the dynamic nature of inputs, but do not directly affect child skill production. I use the hours of school-related leave, the average unemployment insurance tax, the number of children per child care center, the maximum weekly benefit, the average child support distributions, the per cent employed in services, the average subsidized child care expenditure and the average tax liability for a family earning $25,000. I present summary statistics of the variables used to generate the exclusion restrictions in Table F.2.7 and discuss them further in section B.2.1 of the appendix. Last, non-linearities present in the maternal employment and fertility equations and assumptions on the functional forms of the idiosyncratic portion of the error terms in the input and skills equations assist in identification.

One concern with the use of state-level variables as exclusion restrictions is that there may be unobserved state characteristics captured in the error term of the child skill production functions that could be correlated with the exclusion restrictions. Such a correlation would violate the exogeneity condition, rendering the exclusion restrictions invalid and leading to inconsistent parameter estimates. In the case of the exogeneity condition, first, I argue that states are unlikely to differ systematically in average child ability and that this form of bias is especially unlikely to hold when conditioning on key variables such as race, maternal education and household income. Second, I provide empirical evidence that the exogeneity condition is likely to be met by performing a test of overidenitfying restrictions and verifying that the exclusion restrictions pass the test. Additionally, I present further evidence that these forms of endogneiety are unlikely to substantially affect estimates by checking robustness of estimates to the inclusion of school-level permanent unobserved heterogeneity in section 2.5.3.

In order to account for the potential endogeneity of the input decisions with respect to the human capital development and non-cognitive development of the child, I estimate the system of equations jointly with the child cognitive and non-cognitive production functions, in addition to the initial conditions and attrition equations. The system of equations is specified below:

$$ln\Big(\frac{P(I^j_{ist}=0)}{P(I^j_{ist}=1)}\Big) = \delta^j(\Omega_{ist}, X_{ist}, Z_{ist}, \mu^I_{is}, \nu^I_{ist}, \epsilon^I_{ist}) \qquad j=1,2 \tag{2.8}$$

$$H_{ist} = \zeta(\Omega_{ist}, X_{ist}, Z_{ist}, \mu^H_{is}, \nu^H_{ist}, \epsilon^H_{ist}) \tag{2.9}$$

$$ln\Big(\frac{P(E_{ist}=0)}{P(E_{ist}=1)}\Big) = \psi(\Omega_{ist}, X_{ist}, Z_{ist}, \mu^E_{is}, \nu^E_{ist}, \epsilon^E_{ist}) \tag{2.10}$$

$$ln\Big(\frac{P(K_{ist}=k)}{P(K_{ist}=1)}\Big) = \phi(\Omega_{ist}, X_{ist}, Z_{ist}, \mu^K_{is}, \nu^K_{ist}, \epsilon^K_{ist}) \qquad k=2,3 \tag{2.11}$$

$$A^c_{ist} = \gamma^c(A^c_{ist-1}, A^n_{ist-1}, I_{ist}, H_{ist}, E_{ist}, K_{ist}, X_{ist}, \mu^c_{is}, \nu^c_{ist}, \epsilon^c_{ist}) \tag{2.12}$$

$$A^n_{ist} = \gamma^n(A^c_{ist-1}, A^n_{ist-1}, I_{ist}, H_{ist}, E_{ist}, K_{ist}, X_{ist}, \mu^n_{is}, \nu^n_{ist}, \epsilon^n_{ist}) \tag{2.13}$$

$$ln\Big(\frac{P(M_{ist+1} = 1|M_{ist} = 0)}{P(M_{ist+1} = 0|M_{ist} = 0)}\Big) = \beta(A^c_{ist}, A^n_{ist}, I_{ist}, H_{ist}, E_{ist}, K_{ist}, X_{ist}, Z_{ist}, \mu^M_{is}, \nu^M_{ist}, \epsilon^M_{ist}) \tag{2.14}$$

$$ln\Big(\frac{P(I^j_{is0} = 0)}{P(I^j_{is0} = 1)}\Big) = \delta^{j0}(X_{is0}, Z_{is0}, \mu^{I_0}_{is}, \epsilon^{I_0}_{is0}) \qquad j = 1, 2 \tag{2.15}$$

$$H_{is0} = \zeta^0(X_{is0}, Z_{is0}, \mu^{H_0}_{is}, \epsilon^{H_0}_{is0}) \tag{2.16}$$

$$ln\Big(\frac{P(E_{is0} = 0)}{P(E_{is0} = 1)}\Big) = \psi^0(X_{is0}, Z_{is0}, \mu^{E_0}_{is}, \epsilon^{E_0}_{is0}) \tag{2.17}$$

$$K_{is0} = \phi^0(X_{is0}, Z_{is0}, \mu^{K_0}_{is}, \epsilon^{K_0}_{is0}) \tag{2.18}$$

$$A^c_{is0} = \gamma^{c_0}(X_{is0}, Z_{is0}, \mu^{c_0}_{is}, \epsilon^{c_0}_{is0}) \tag{2.19}$$

$$A_{is0}^{n} = \gamma^{n_0}(X_{is0}, Z_{is0}, \mu_{is}^{n_0}, \epsilon_{is0}^{n_0}) \tag{2.20}$$

The error term in each equation can be decomposed into three components: permanent unobserved heterogeneity of the mother/child, the μs, time-varying unobserved heterogeneity of the mother/child, the νs as well as decision-specific shocks, the ϵs. Shocks are superscripted by alternatives to account for unobserved heterogeneity having differing effects on child skill formation and maternal input decisions. The error terms are correlated across equations through permanent characteristics of the mother/child, and time-varying unobserved characteristics of the mother/child, the νs, and across time through permanent unobserved characteristics of the mother/child, the μs. Whereas I assume the permanent unobserved heterogeneity is drawn in period 0 and fixed over time, I assume ν_{ist} is a time-varying shock that is drawn each period and affects all alternatives and child skill formation. An example would be a health shock to the child that affects child skill formation as well as the mother's decision to work, fertility choices, and her home input and involvement decisions. I assume ν_{ist} is not serially correlated conditional on permanent unobserved heterogeneity.[14] Lastly, I assume ϵ_{ist} contains an alternate or outcome specific random shock that is uncorrelated across individuals and over time. I assume ϵ_{ist} is distributed $\sim N(0, \sigma^2)$ for continuous equations and Type 1 Extreme Value for discrete equations, however, I do not make functional form assumptions on the distribution of the unobserved heterogeneity terms.[15]

Estimation

I jointly estimate the above system of equations using full information maximum likelihood. The parameter vector θ is estimated jointly with the number of permanent unobserved types of

[14] I provided some indication that this is likely to hold by performing and rejecting an Arellano-Bond test of serial correlation in the differenced error terms within a System Generalized Method of Moments framework.

[15] Using Monte Carlo Simulations, Mroz (1999) showed that the method employed here has been shown to perform as well as maximum likelihood estimators in terms of precision and bias when the true model is jointly normal and normality is assumed. Additionally, the method here has been shown to be more robust to violations of the normality assumption.

mother/child and the probability weight for each type as well as the number of time-varying unobserved heterogeneity types and their respective probability weights. The unconditional likelihood function for a mother whose child i is in school s is given by the joint probability of observing the cognitive and non-cognitive skills and the parental inputs:

$$\begin{aligned}
\mathcal{L}_{is}(\theta,\mu_m,\nu_{qt},\eta_m,\omega_q) = \sum_{m=1}^{M}\eta_m \Bigg\{ & f_{A_0^c}(A_0^c|\mu_m^{A_0^c}) f_{A_0^n}(A_0^n|\mu_m^{A_0^n}) f_{K_0}(K_0|\mu_m^{K_0}) f_{H_0}(H_0|\mu_m^{H_0}) \\
& \prod_{e=0}^{1}\left[Pr(E_0=e|\mu_m^{E_0})^{1(E_0=e)}\right]\prod_{i=0}^{1}\left[Pr(I_0^1=i|\mu_m^{I_0^1})^{1(I_0^1=i)}\right]\prod_{i=0}^{1}\left[Pr(I_0^2=i|\mu_m^{I_0^2})^{1(I_0^2=i)}\right] \\
& \sum_{q=1}^{Q}\omega_q\prod_{t=1}^{T}\Bigg\{ f_{A_t^c}(A_t^c|\mu_m^{A_t^c},\nu_{qt}^{A_t^c}) f_{A_t^n}(A_t^n|\mu_m^{A_t^n},\nu_{qt}^{A_t^n}) f_{H_t}(H_t|\mu_m^{H_t},\nu_{qt}^{H_t}) \\
& \left[\prod_{e=0}^{1}\left[Pr(E_t=e|\mu_m^{E_t},\nu_{qt}^{E_t})^{1(E_t=e)}\right]\right]\left[\prod_{i=0}^{1}\left[Pr(I_t^1=i|\mu_m^{I_t^1},\nu_{qt}^{I_t^1})^{1(I_t^1=i)}\right]\right] \\
& \left[\prod_{i=0}^{1}\left[Pr(I_t^2=i|\mu_m^{I_t^2},\nu_{qt}^{I_t^2})^{1(I_t^2=i)}\right]\right] \\
& \left[\prod_{k=1}^{3}\left[Pr(K_t=k|\mu_m^{K_t},\nu_{qt}^{K_t})^{1(K_t=k)}\right]\right]\left[\prod_{m=0}^{1}\left[Pr(M_{t+1}=m|\mu_m^{M_{t+1}},\nu_{qt}^{M_{t+1}})^{1(M_{t+1}=m)}\right]\right]\Bigg\}\Bigg\}
\end{aligned} \tag{2.21}$$

where η^m is the probability of a mother/child being type m and ω_q is the probability of a type q shock.

The likelihood for the entire sample is:

$$\prod_{i=1}^{N}\mathcal{L}_{is}(\theta,\mu_m,\nu_{qt},\eta_m,\omega_q) \tag{2.22}$$

2.5 Results

2.5.1 Production Function Estimates

I present the results for the FIML specification in Column 2 in Tables 2.1, 2.2, and 2.3, for reading, math and non-cognitive skills, respectively, including the unobserved heterogeneity terms along with the baseline OLS results in Column 1 for comparison. I use 4 points of support for permanent unobserved heterogeneity and 3 points of support for time-varying unobserved heterogeneity with the mass points and probability weights presented in the table 2.4 below, where Column 1 gives the probabilities for permanent unobserved heterogeneity types, Column 2 gives the mass point of each permanent unobserved heterogeneity type, with the standard errors reported in brackets, Column 3 gives the probabilities for the time-varying unobserved heterogeneity types, and Column 4 gives the mass point of each time-varying unobserved heterogeneity type, with the standard errors reported in brackets. Prior to comparing the OLS and FIML coefficients, I first test whether there is a statistically significant improvement in the fit of the model as measured by the value of the likelihood function from including the permanent and time-varying unobserved heterogeneity terms by performing a likelihood ratio test. I outline the details of the test in Appendix section C.2.1 and discuss the conclusions here. Based on the results of the test, I find that the model including permanent unobserved heterogeneity results in a better fit compared with the model excluding unobserved heterogeneity. This finding further underscores the importance of accounting for unobserved heterogeneity when identifying parameters of interest.

I find positive and statistically significant effects of a parent volunteering in school on math, reading and non-cognitive skills of 0.04, 0.04, and 0.05 standard deviations, respectively. To get a sense of the magnitude of these estimates, the effects are comparable to roughly 17%, 19%, and 64% of the direct effect of a mother having a bachelor's degree or higher education as opposed to a high school or less than high school education. The effect sizes in the FIML specification where I correct for the endogeneity of parental involvement and other related input decisions are approximately 52%, 44%, and 9% larger as compared with the OLS results for math, reading, and non-cognitive skills, respectively. I find evidence that both permanent and time-varying unobserved heterogeneity matter for the realization of math, reading and non-cognitive skills with all terms statistically significant at the 1% level.

I find that attending a parent-teacher conference has a negative and statistically significant effect on reading skills in the baseline OLS specification of approximately 0.05 standard deviations, however, I find that the effect becomes statistically insignificant when the endogeneity of the decision is accounted for. Conversely, I find that attending a parent-teacher conference has a statistically insignificant effect on math skills in the baseline OLS specification, however, when the endogeneity is accounted for I find a positive and statistically significant effect of 0.04 standard deviations, though only at the 10% level, equivalent to approximately 19% of the effect of having a mother with a bachelor's or higher education as opposed to high school or less than high school. These two results seem to suggest evidence of a negative selection into attending parent-teacher conferences whereby parents of inherently lower skilled children are more likely to participate in parent-teacher conferences, highlighting the importance of controlling for the effect of unobserved characteristics when quantifying the effects of the parental involvement decisions. Last, I find a diminished effect of attending parent-teacher conferences on non-cognitive skills when comparing OLS and FIML estimates. Attending a parent teacher conference has a negative effect of of 0.07 standard deviations under OLS compared with 0.06 standard deviations under FIML, representing a decrease in the effect of 14%. While the recovered estimates of the effects of parental involvement are largely intuitive, the negative effect of attending a parent-teacher conference on a child's non-cognitive skills is puzzling. One possible way in which attending a parent-teacher conference could lead to negative effects on a child's non-cognitive skills is if parents react negatively to the teacher's report of their child's non-cognitive skills, thus causing them to decline further. One way to test this would be to evaluate the effect of attending a parent-teacher conference on non-cognitive inputs, however, a lack of data on non-cognitive inputs precludes this.

I find a positive direct effect of home inputs on math and reading scores of 0.04 and 0.04 standard deviations, corresponding to roughly 17% and 17%, of the direct effect of the mother having a bachelors or higher relative to high school or less than high school educational attainment, respectively. I, however, do not find a direct effect of home inputs on non-cognitive skills. This lack of an effect could be due to the definition of home inputs being skewed towards educational inputs, largely due to an inconsistency in the report of non-cognitive inputs across waves. In their paper, Fiorini and Keane (2014) consider a broader measure of home inputs that includes measures of non-cognitive inputs such as warmth and discipline and find that these constructs affect their measures of non-cognitive skills.

I do not find evidence to suggest that maternal employment has a direct effect on child skill accumulation once the endogeneity of the maternal input decision is accounted for. The number of siblings has a negative effect on both math and reading skills possibly due to parental time dilution. By contrast, the number of siblings has a positive effect on non-cognitive skills, potentially due to increases in inter-personal skills gained through interacting with siblings.

Table 2.1: Child Reading Skill Production Function under OLS and Full Information Maximum Likelihood

	(1) OLS		(2) FIML	
Lag Reading Score	0.6202***	(0.0067)	0.5090***	(0.0089)
Lag Non-Cognitive Score	0.1394***	(0.0062)	0.0655***	(0.0069)
Mother Not Employed	−0.0243*	(0.0125)	−0.0158	(0.0138)
Volunteering	0.0294**	(0.0119)	0.0423***	(0.0144)
Conference	−0.0475**	(0.0213)	−0.0144	(0.0230)
Home Inputs	0.0546***	(0.0062)	0.0421***	(0.0114)
No. of Siblings	−0.0336***	(0.0053)	−0.0335***	(0.0061)
Bachelors or Higher	0.1910***	(0.0173)	0.2470***	(0.0196)
Mother/Child Type 1			1.1219***	(0.0843)
Mother/Child Type 2			0.8281***	(0.0574)
Mother/Child Type 3			0.8737***	(0.0950)
Time-Varying Type 1			1.8321***	(0.0853)
Time-Varying Type 2			−0.9884***	(0.0825)
Observations	21750		21750	

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors are in parentheses. The full set of controls have been suppressed for brevity. The full set of controls are lagged reading and non-cognitive skills, child gender, mother's age, mother's age squared, mother's education status, annual household income (000's), child race, family structure, primary language spoken at home, year dummies and missing data indicators. * refers to statistical significance at the 10% level, ** refers to statistical significance at the 5% level, *** refers to statistical significance at the 1% level.

These effects may seem relatively small in magnitude, but they are largely consistent with effect sizes observed when measuring the effect of similar inputs in much of the literature, particularly at this stage of a child's life. For instance Del Bono (2016) finds that a 1 standard deviation increase in education inputs, a construct similar to home inputs, leads to a 0.04 standard deviation increase in verbal skills when the child is aged 7. Additionally, it is important to note that the effect sizes of other characteristics such as maternal education, race, and household income are relatively small in magnitude. Looking at the initial conditions in Appendix tables F.2.15 to F.2.17, it becomes apparent why the effect sizes are relatively small. Here we see large and statistically significant

Table 2.2: Child Math Skill Production Function under OLS and Full Information Maximum Likelihood

	(1) OLS		(2) FIML	
Lag Math Score	0.6938***	(0.0078)	0.5825***	(0.0100)
Lag Non-Cognitive Score	0.1336***	(0.0064)	0.0625***	(0.0069)
Mother Not Employed	−0.0220*	(0.0128)	−0.0215	(0.0139)
Volunteering	0.0257**	(0.0120)	0.0390***	(0.0143)
Conference	−0.0040	(0.0217)	0.0407*	(0.0240)
Home Inputs	0.0484***	(0.0064)	0.0347***	(0.0116)
No. of Siblings	−0.0192***	(0.0052)	−0.0138**	(0.0060)
Bachelors or Higher	0.1579***	(0.0179)	0.2093***	(0.0202)
Mother/Child Type 1			1.1081***	(0.0737)
Mother/Child Type 2			0.7714***	(0.0530)
Mother/Child Type 3			0.8380***	(0.0909)
Time-Varying Type 1			2.0434***	(0.1158)
Time-Varying Type 2			−0.9642***	(0.0997)
Observations	21750		21750	

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors are in parentheses. The full set of controls have been suppressed for brevity. The full set of controls are lagged math and non-cognitive skills, child gender, mother's age, mother's age squared, mother's education status, annual household income (000's), child race, family structure, primary language spoken at home, year dummies and missing data indicators. * refers to statistical significance at the 10% level, ** refers to statistical significance at the 5% level, *** refers to statistical significance at the 1% level.

Table 2.3: Child Non-Cognitive Skill Production Function under OLS and Full Information Maximum Likelihood

	(1) OLS		(2) FIML	
Lag Reading Score	0.0802***	(0.0047)	0.0397***	(0.0067)
Lag Non-Cognitive Score	0.5228***	(0.0063)	0.5027***	(0.0074)
Mother Not Employed	0.0041	(0.0118)	0.0062	(0.0116)
Volunteering	0.0486***	(0.0115)	0.0531***	(0.0118)
Conference	−0.0719***	(0.0206)	−0.0647***	(0.0201)
Home Inputs	0.0150**	(0.0059)	0.0085	(0.0079)
No. of Siblings	0.0225***	(0.0049)	0.0218***	(0.0049)
Bachelors or Higher	0.0613***	(0.0164)	0.0833***	(0.0169)
Mother/Child Type 1			0.3480***	(0.0373)
Mother/Child Type 2			0.2298***	(0.0283)
Mother/Child Type 3			0.2199***	(0.0455)
Time-Varying Type 1			0.3286***	(0.0480)
Time-Varying Type 2			−0.2757***	(0.0390)
Observations	21750		21750	

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors are in parentheses. The full set of controls have been suppressed for brevity. The full set of controls are lagged reading and non-cognitive skills, child gender, mother's age, mother's age squared, mother's education status, annual household income (000's), child race, family structure, primary language spoken at home, year dummies and missing data indicators. * refers to statistical significance at the 10% level, ** refers to statistical significance at the 5% level, *** refers to statistical significance at the 1% level.

effects of race and maternal education on initial math and reading skills. This suggests that after controlling for the effect of this initial skill indirectly through the inclusions of the lagged score, the effects of parental involvement and other inputs are marginal effects and thus relatively small.

Table 2.4: Mass Points and Probabilities-Baseline Model

	Mother/Child		Time-Varying	
Type	Probability	Mass Point	Probability	Mass Point
1	0.1771	0.0000	0.8856	0.0000
		(0.0000)		(0.0000)
2	0.1991	0.1169	0.0188	−3.8529
		(0.1698)		(0.1090)
3	0.5517	1.1362	0.0956	−2.2260
		(0.0996)		(0.2201)
4	0.0722	−0.8975		
		(0.1375)		

Notes: Standard errors are in parentheses.

2.5.2 Input Decisions

Appendix Tables F.2.8-F.2.13 show the approximation to the decision rules for the parental involvement decisions-volunteering at school and attending a parent-teacher conference, home inputs, maternal non-employment, as well as the decisions to increase siblings and decrease siblings, respectively. Column 1 in each specification gives baseline OLS result and Column 2 gives the results accounting for individual level heterogeneity by including individual level permanent and time-varying unobserved heterogeneity. Since the main variable of interest is parental involvement, I discuss the determinants of the input decisions in detail below. I also briefly discuss some of the dynamics of the input decisions to show evidence of the importance of the dynamic interdependence of inputs over time.

The main identified determinants of volunteering at school mirror some of what has been found in the previous literature and are largely consistent with national trends. Parents are more likely to volunteer if their child has higher prior cognitive and non-cognitive skills. This could be due to children, or teachers of children, with higher cognitive or non-cognitive skills being more likely to ask their parents to volunteer, or a lower associated cost and/or higher utility associated with volunteering if the child is higher-achieving. A higher level of maternal education and a higher income status are both associated with a higher probability of volunteering, possibly due to more educated or wealthier mothers facing fewer barriers to participation and/or heterogeneous preferences for child skill along these same dimensions as captured by the αs in the theoretical model in Section 2.3. Black mothers, Hispanic mothers, mothers from other races, and non-English speaking households are all associated with a lower probability of volunteering which may point to heterogeneous barriers and/or preferences by race or language (Aronson (1996)) and/or a cultural reluctance to interfere in what is viewed as the domain of teachers (Lareau (2000)). Having a mother who was not employed in the prior period has a positive effect on the volunteering decision suggesting that binding time constraints may be a key factor affecting volunteering. Surprisingly, the number of children in the prior period does not seem to affect the probability of volunteering at school despite the potential for there to be binding time constraints. Parents are also less likely to volunteer in later grades, potentially due to the probability of them being more likely to be employed in later grades, and thus being more time constrained. I find support for this hypothesis by analyzing the maternal non-employment decision in Appendix table F.2.11, which shows some evidence that mothers are less likely to not be employed in later grades. I find evidence that the school-related leave policies, the child tax credit, and state-level expenditure on subsidized child care all positively affect the probability of volunteering. I find that unobserved heterogeneity matters for the volunteering decision with mother/child type 3 and time-varying type 2 both statistically significant.

The determinants of attending a parent-teacher conference differ substantially from those of the decision to volunteer, most notably in the effect of the child's prior skill level. In contrast to volunteering, having a child with lower prior cognitive and non-cognitive skills is associated with an increase in the probability of attending a parent-teacher conference. This finding supports the presence of negative selection inherent in the parent-teacher conference decision whereby parents of lower skilled children are more likely to attend parent-teacher conferences leading to a downward bias in the effect. I also find evidence of some racial differences compared with volunteering at school with black parents more likely to attend a parent-teacher conference. Similar to volunteering at school, I find that parents are less likely to attend a parent-teacher conference in later grades, perhaps for the same reason explained previously. I find evidence that the school-related leave policies and the child tax credit affects the probability of attending a parent-teacher conference, in addition to the state level expenditure on subsidized child care. With the exception of Time-Varying Shock Type 1, there is little other evidence to suggest that unobserved heterogeneity matters for the decision to attend a parent-teacher conference.

The difference in participation by child's prior skill levels seems to suggest that parents participate in different forms of involvement depending on where their children lie in the skills distribution and/or that teachers encourage parents to participate in different forms of activities depending on where their children lie in the skills distribution. The reason for this difference could be that attending a parent-teacher conference may be viewed as a remedial, hence parents of lower skilled children being more likely to attend, whereas volunteering at school may be viewed as a more general form of involvement.

The determinants of home inputs have been explored previously in the economics literature (See for example Del Boca (2014) and Fiorini and Keane (2014)). The salient determinants identified from the home input decisions are largely consistent with the prior literature. Parents of children with higher prior reading scores have a higher level of home inputs, however, I do not find an effect for prior non-cognitive skills. As mentioned previously, this lack of an effect could be due to the definition of home inputs being skewed towards educational inputs, largely due to an inconsistency in the report of non-cognitive inputs across waves. Since we did not find an effect of home inputs on non-cognitive skills (See table 2.3), then we would not necessarily expect parents to adjust these inputs in response to prior realizations of non-cognitive test scores. Parents invest a higher level of home inputs if the child is a girl, relative to a boy, consistent with the gender differences highlighted by Fiorini and Keane (2014) who found that parents spend more time in educational activities with girls whilst boys spend more time on media activities. More educated mothers have a higher level of home inputs, this could be due to differences in the cost of home inputs, differences in preferences for child quality and/or differences in the productivity of home inputs by maternal education status. Interestingly single parents and households who do not speak English as the primary language have a higher level of home inputs, perhaps due to them having a lower propensity to be employed (See F.2.11). The school-related leave policy has a direct effect on home inputs, potentially through conveying the importance of parents as active agents in their child's education process, leading to an increase in home inputs. I find evidence that permanent unobserved heterogeneity matters for home inputs with both mother/child types 1 and 2 affecting the level of home inputs, but I do not find effects for time-varying unobserved heterogeneity.

The determinants of the maternal employment and fertility decisions, largely enter with the expected signs. One thing to note, is the large degree of persistence inherent in employment states in that if an individual is not employed in period $t-1$, there is a strong probability that that individual would not be employed in period t. With the exception of a statistically significant effect of mother/child unobserved heterogeneity type 3 in the maternal employment decision, I do not find evidence so suggest that unobserved heterogeneity matters for the maternal employment and fertility decisions.

I find support for various forms of dynamic inter-dependence of input decisions. For instance, having a mother who is not employed in the previous period has positive effects on contemporaneous volunteering and home input decisions. This inter-temporal effect could be due to the persistence in unemployment states cited previously in that if the mother is not employed in the previous period she is unlikely to be employed in the current period and thus have more time available for home inputs and volunteering at school. Interestingly, I find evidence that the lagged level of home inputs affects volunteering at school, and to a lesser extent home inputs, whereby a 1 standard deviation increase in home inputs leads to a 0.08 increase in the probability of volunteering at school, roughly 16% of the effect of having a mother with a bachelors or higher relative to high school or less education. This could be due to parents who spend more time with their children at home being more aware of opportunities to volunteer at school. I also find evidence of an indirect effect of volunteering, and to a lesser extent, attending a parent-teacher conference, on parental on home inputs whereby a 1 standard deviation increase in lagged volunteering is associated with a 0.07 standard deviation increase in contemporaneous home inputs. The effect of lagged volunteering on home inputs is roughly 39% of direct effect of having a mother with a bachelor's or higher relative to having a mother with high school or less educational attainment. This effect has previously been documented in the literature, most notably by (Wherry (2004)), who hypothesizes that through interacting with teachers, parents are better able to establish an environment more conducive to learning at home, leading to an increase in the quantity and quality of home inputs and subsequently child skill production. Evidence of these dynamic effects underscores the importance of modeling related input decisions in quantifying the total impact of the parental involvement decision and in quantifying the effect of various policy simulations on life-cycle skill accumulation.

2.5.3 Robustness Checks

School Correlated Random Effects

In order to account for the possibility that there are unobserved characteristics at the school (or state) level that can both influence parental input decisions and child skill formation, I include school-level permanent unobserved heterogeneity parameters in my input decisions and skill production functions and rely on variation within a school over time to identify my parameters of interest. In addition to accounting for unobserved school inputs, the inclusion of school-level permanent unobserved heterogeneity also accounts for potential unobserved state-level inputs as students within a school are necessarily nested within the same state. I employ the correlated random effects method outlined in section D.2.1 in table 2.5 below with the associated unobserved heterogeneity types and their corresponding probability weights presented in table 2.6. The correlated random effects model assumes that the unobserved heterogeneity, in this case, the school-level unobserved heterogeneity can be modeled as a function of the school level time-average of the included regressors and includes these time-averages as regressors in the equations along with their contemporaneous counterparts. We can compare this approach with a fixed effect model where no restriction is placed on the relationship between the school-level unobserved heterogeneity and the regressors and instead of controlling for the school-level time-average of the included regressors, consistent estimates are recovered after demeaning the terms through subtracting the corresponding school-level time-average. Incidentally, though the correlated random effects and fixed effects deal with the endogeneity problem in different ways, the parameters recovered on the time-varying variables in the fixed effect and correlated random effect models will be the same.

For the correlated random effects model, I estimate four points of support for the permanent unobserved heterogeneity and three points of support for the time-varying unobserved heterogeneity and present the mass points along with their associated probabilities in table 2.6 below. Similar to the results without correlated random effects, I find that all types of unobserved heterogeneity matter for skill formation across all skills with all types statistically significant at the 1% level.

Table 2.5: Math, Reading and Non-Cognitive Skills-School Correlated Random Effects

	(1) Math		(2) Reading		(3) Non-Cognitive	
Volunteer	0.0298^{*}	(0.0156)	0.0183	(0.0157)	0.0595^{***}	(0.0128)
Conference	-0.0360	(0.0297)	-0.0653^{**}	(0.0283)	-0.0912^{***}	(0.0234)
Mother/Child Type 1	-0.2912^{***}	(0.0478)	-0.2619^{***}	(0.0494)	-0.1528^{***}	(0.0388)
Mother/Child Type 2	-1.0410^{***}	(0.0824)	-1.0438^{***}	(0.0907)	-0.3363^{***}	(0.0381)
Mother/Child Type 3	-0.3159^{***}	(0.0298)	-0.2693^{***}	(0.0372)	-0.1045^{***}	(0.0252)
Time-Varying Type 1	0.9926^{***}	(0.0970)	1.0221^{***}	(0.0805)	0.2918^{***}	(0.0385)
Time-Varying Type 2	3.0513^{***}	(0.1818)	2.8696^{***}	(0.1403)	0.6318^{***}	(0.0627)
Observations	21750		21750		21750	

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors are in parentheses. The full set of controls have been suppressed for brevity. The full set of controls are lagged math, reading, and non-cognitive skills, child gender, mother's age, mother's age squared, mother's education status, annual household income (000's), child race, family structure, primary language spoken at home, year dummies and missing data indicators. * refers to statistical significance at the 10% level, ** refers to statistical significance at the 5% level, *** refers to statistical significance at the 1% level.

Table 2.6: Mass Points and Probabilities-School Correlated Random Effects

	Mother/Child		Time-Varying	
Type	Probability	Mass Point	Probability	Mass Point
1	0.1851	0.0000	0.0930	0.0000
		(0.0000)		(0.0000)
2	0.0916	-0.7032	0.8891	2.2577
		(0.1333)		(0.2016)
3	0.1828	-0.0128	0.0179	-1.6464
		(0.1822)		(0.2244)
4	0.5405	1.0716		
		(0.0910)		

Notes: Standard errors are in parentheses.

With the exception of the effect on reading skills, the results on volunteering are largely consistent with the model that does not account for school-level unobserved heterogeneity, however, the results on attending parent-teacher conferences show some inconsistencies. In the context of a likely relatively low degree of variation in attending parent teacher conferences within a school and over time (See Table F.2.4), caution should be used in interpreting these coefficients.

2.5.4 Heterogeneity Analysis

In this section, I explore whether the different measures of parental involvement have different effects across sub-groups of interest. I focus on heterogenous effects by (prior) skill level to compare my results to the literature on dynamic complementarities (Cunha and Heckman (2008)). I repeat the analysis by including an interaction term between the measures of parental involvement and lagged cognitive and non-cognitive skills to determine whether parental involvement has differential effects based on prior child achievement. I present the results in Table 2.7 and the mass points for the unobserved heterogeneity types and their associated probabilities in table 2.8 below. For ease of interpretation, I de-mean the cognitive and non-cognitive skills in the interaction terms. I find evidence that volunteering at school has a greater effect for children with lower prior reading and math skills but do not find evidence that parental involvement has differential effects based on the child's prior non-cognitive skills. I also find less negative effects of attending parent-teacher conferences on non-cognitive skills, but only for children towards the upper end of the non-cognitive skills distribution. I estimate four points of support for the permanent unobserved heterogeneity and three points of support for the time-varying unobserved heterogeneity and present the mass points along with their associated probabilities in table 2.8. Similar to the results without the inclusion of the interaction terms, I find that both permanent and time-varying unobserved heterogeneity matter with all types statistically significant at the 1% level for math, reading and non-cognitive skills. Given that I find substantial heterogeneity, going forward, I use the results accounting for heterogeneity as my main results.

2.5.5 Life-Cycle Effects

Since the measures of parental involvement appear in several places throughout the model, namely directly as inputs in the skill equations and indirectly as lags in the contemporaneous input decisions, it is difficult to quantify the effects of parental involvement over the life-cycle of the child. To get a sense of the life-cycle effect of parental involvement, I simulate the life-cycle

Table 2.7: Heterogeneous Effects of Parental Involvement on Math, Reading and Non-Cognitive Skills

	(1) Math		(2) Reading		(3) Non-Cognitive	
Lag Score	0.7110***	(0.0284)	0.5742***	(0.0293)	0.3677***	(0.0464)
Volunteer	0.1212***	(0.0178)	0.1198***	(0.0180)	0.0613***	(0.0118)
Volunteer*Lag Score	−0.0638***	(0.0060)	−0.0556***	(0.0064)	0.0125	(0.0117)
Conference	0.0572*	(0.0310)	−0.0210	(0.0317)	−0.0699***	(0.0212)
Conference*Lag Score	−0.0121	(0.0117)	0.0143	(0.0121)	0.0598***	(0.0224)
Mother/Child Type 1	−0.2846***	(0.0420)	−0.2572***	(0.0438)	−0.1388***	(0.0373)
Mother/Child Type 2	−0.3235***	(0.0307)	−0.2782***	(0.0377)	−0.1074***	(0.0248)
Mother/Child Type 3	−1.0593***	(0.0764)	−1.0680***	(0.0877)	−0.3394***	(0.0375)
Time-Varying Type 1	3.1435***	(0.1561)	2.9405***	(0.1239)	0.6293***	(0.0617)
Time-Varying Type 2	1.0389***	(0.0854)	1.0505***	(0.0703)	0.2801***	(0.0392)
Observations	21750		21750		21750	

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors are in parentheses. The full set of controls have been suppressed for brevity. The full set of controls are lagged math, reading, and non-cognitive skills, child gender, mother's age, mother's age squared, mother's education status, annual household income (000's), child race, family structure, primary language spoken at home, year dummies and missing data indicators. * refers to statistical significance at the 10% level, ** refers to statistical significance at the 5% level, *** refers to statistical significance at the 1% level.

Table 2.8: Mass Points and Probabilities-Heterogeneity Analysis

	Mother/Child		Time-Varying	
Type	Probability	Mass Point	Probability	Mass Point
1	0.1920	0.0000	0.0827	0.0000
		(0.0000)		(0.0000)
2	0.0994	−0.6583	0.0180	−1.5274
		(0.1275)		(0.1833)
3	0.5279	1.0112	0.8993	2.3861
		(0.0991)		(0.1629)
4	0.1807	−0.0611		
		(0.1800)		

Notes: Standard errors are in parentheses.

change of having a parent who volunteers at school each period, and compare the trajectories of cognitive and non-cognitive skill accumulation with that of a parent who never volunteers at school. Similarly, I simulate the cognitive and non-cognitive trajectories of a parent who always attends parent-teacher conferences and compare them with that of a parent who never attends parent-teacher conferences. In addition to the direct effect of parental involvement on child skill formation, the life-cycle effects take into account the dynamics of input decisions by allowing for fertility, maternal employment and home inputs to change in response to the change in parental involvement due to mechanisms discussed previously. I gave a cursory treatment to the simulation procedure here, but discuss it more thoroughly in Appendix section E.2.1. I present the results for volunteering in Table 2.9 and for attending a parent-teacher conference in Table 2.10. As can be seen from Table 2.9, the life-cycle effects of volunteering at school are largely concentrated in the accumulation of non-cognitive skills, particularly in grade 3, with similar patterns observed for math and reading skills. By contrast, due to the negative effect of attending a parent teacher-conference on non-cognitive skills, there are negative effects on non-cognitive skill accumulation immediately and over time. The effect of parent-teacher conferences on the life-cycle accumulation of math and reading skills is relatively small.

Table 2.9: Life-Cycle Effects of Volunteering vs Not Volunteering

	Grade 1	Grade 2	Grade 3
Math	0.123	0.216	0.283
Reading	0.121	0.195	0.239
Non-Cognitive	0.061	0.088	0.102
Observations	8550	7500	5600

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset.

Table 2.10: Life-Cycle Effects of Attending a Parent-Teacher Conference vs Not Attending a Parent-Teacher Conference

	Grade 1	Grade 2	Grade 3
Math	0.048	0.072	0.085
Reading	−0.032	−0.061	−0.083
Non-Cognitive	−0.075	−0.107	−0.121
Observations	8550	7500	5600

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset.

2.6 Policy Simulations

Since a key question of interest is the effect of these state-school related leave policies on student outcomes, in this section I use the estimates obtained from the full information maximum likelihood estimator in the preferred model to evaluate the effects of these policies. The policies have been shown to affect the volunteering, conference and home inputs decisions directly (See tables F.2.8 to F.2.10), and subsequently these inputs have been show to affect cognitive and non-cognitive outcomes (See tables 2.1 to 2.3). Although, the policies do not affect the maternal employment, and fertility decisions directly (See tables F.2.11-F.2.13), there may be indirect effects on these input decisions both through the dynamic interdependence of inputs as well as the dependence of contemporaneous employment and fertility decisions on lagged score realizations which in turn depend on prior volunteering, conference and home input decisions. By accounting for both the direct effect of the policies on the volunteering, conference and home input decisions, in addition to the potential indirect effects on the employment and fertility decisions, I am able to quantify both the direct and indirect mechanisms through which the policy can affect outcomes.

2.6.1 State School-Related Leave Policies

When surveyed about the reasons preventing parents from getting involved in their child's schooling as shown in figure 2.2, the primary reason given is "cannot get the time off from work" (approximately 37 percent in Kindergarten and 32 percent in Grade 2), followed by "inconvenient meeting time" (approximately 25 percent in Kindergarten and 22 percent in Grade 2), suggesting binding time constraints are one of the primary reasons hindering parents' ability to participate in school-based activities.[16]

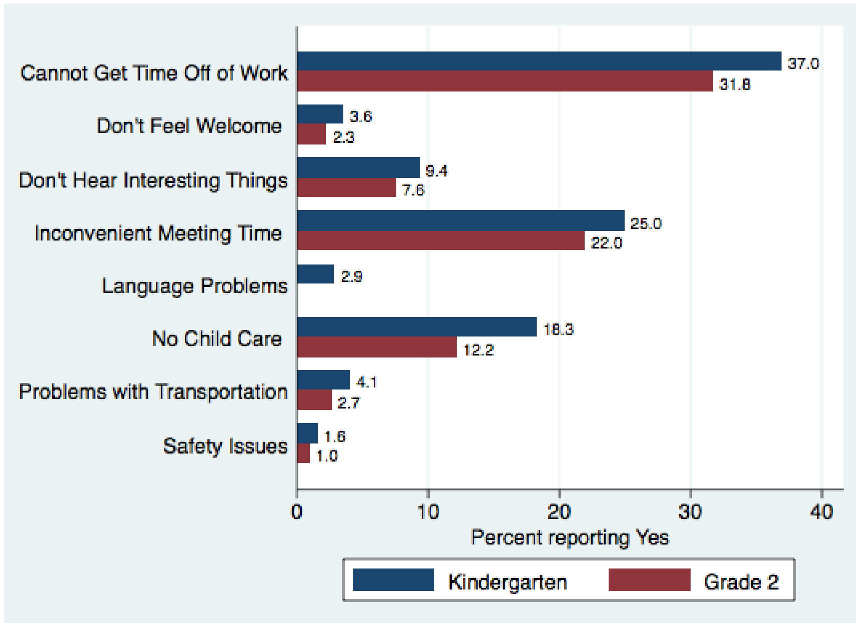


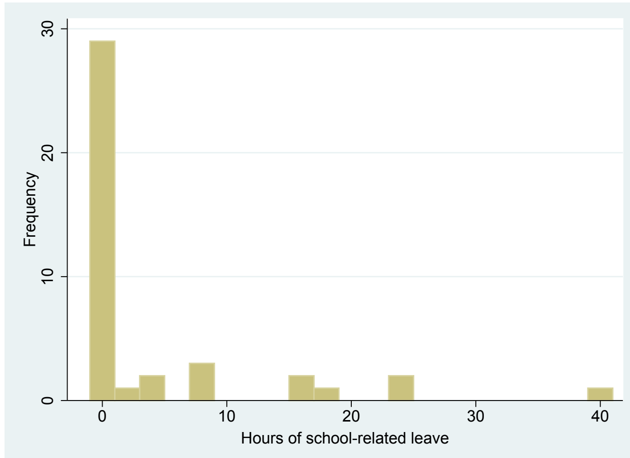
Figure 2.2: Parental Reasons for Non-Participation

In response to this, some states have implemented a policy that allows parents time off from their place of work to participate in their child's schooling. The number of hours allowed off ranges from 2 hours to 40 hours with the distribution presented in figure 2.3.

Section B.2.1 in the Appendix further discusses these policies. The primary effect of these policies is through relaxing the time-constraints of parents, allowing them to increase their level of parental involvement; though there may be additional effects through conveying the importance of parents as active agents in their child's schooling process, potentially altering how parents value education, leading them to adjust their inputs. Despite the relatively widespread implementation of the policy, the effects of the policy on student outcomes have not yet been formally quantified. In the sections that follow, I examine the effect of the policy on a child's math, reading and non-cognitive skills and evaluate some of the potential mechanisms through which these policies can affect outcomes.

[16]The question comes from the parent questionnaire in the ECLS-K and is asked in the Spring of Kindergarten and the Spring of Grade 2 as follows: "This year have the following reasons made it harder for you to participate in activities at your child's school"?

Figure 2.3: Distribution of Number of Hours of School-Related Leave Across States



2.6.2 Policy Simulations

Using the estimated dynamic model in section 2.4, I can evaluate the long term effects of increasing the number of hours parents are allowed off on cognitive and non-cognitive outcomes. These simulations will allow me not only to quantify the total effects of the policy simulation, but also allow me to directly identify and quantify the mechanisms through which the policy is affecting outcomes.

Prior to conducting policy simulations, it is important to check that the estimated model fits the patterns observed in the data to ensure the baseline effects are comparable to what is observed in the data and to give credence to the estimated parameters. Table 2.11 shows the observed and simulated values for maternal input decisions and child skill formation for each wave of the data. As can be seen from the table, the model fits the observed patterns in the data well, though to a lesser extent in the final period, presumably due to the degree of non-random attrition occurring between the last two waves (See Appendix Table F.2.14), where we see that parents who are less likely to volunteer and attend a parent-teacher conference are all more likely to attrit. Additionally, I find that there is substantial unobserved heterogeneity in the decision to attrit with all types affecting the probability of attrition.

Table 2.11: Actual and Simulated Model Fit

Variable	First Grade		Second Grade		Third Grade	
	Observed	Simulated	Observed	Simulated	Observed	Simulated
Continuous						
Math	3.37	3.22	4.77	4.46	5.76	5.29
	(1.44)	(1.14)	(1.30)	(1.26)	(1.17)	(1.35)
Reading	3.50	3.44	4.65	4.49	5.38	5.12
	(1.43)	(1.10)	(1.15)	(1.12)	(1.03)	(1.16)
Non-Cognitive	0.06	0.07	0.06	0.05	0.08	0.05
	(0.98)	(0.94)	(0.98)	(0.88)	(0.97)	(0.88)
Home Inputs	-0.04	-0.04	-0.09	-0.10	-0.11	-0.14
	(0.95)	(0.88)	(0.92)	(0.90)	(0.89)	(0.91)
Discrete						
Volunteer	59.64	58.95	56.74	57.47	56.88	57.45
Conference	93.93	93.91	92.76	93.78	92.06	93.40
Mother Not Employed	32.27	32.14	29.07	29.26	26.32	26.68
Decrease Siblings	1.68	1.64	2.59	2.97	2.37	2.61
Increase Siblings	5.06	5.08	4.91	5.17	4.09	4.36
Observations	8550	8550	7500	7500	5600	5600

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard deviations are reported in parentheses. Standard deviations on discrete variables are suppressed for brevity.

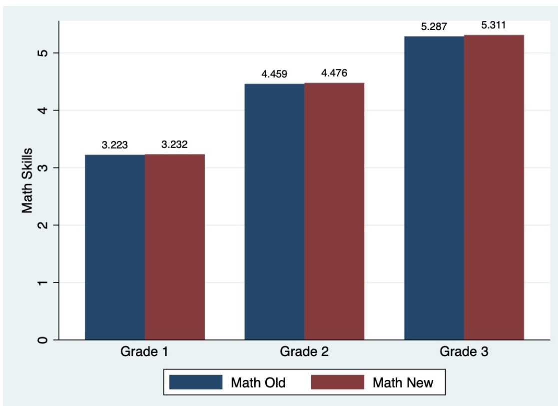
In this policy simulation, I evaluate the effect of changing the number of hours parents are allowed off of their place of work to participate in their child's school to the current maximum policy in place of 40 hours, and examine the life-cycle effect of this change. As can be seen from the input decisions in tables F.2.8-F.2.13 and the outcome equations in tables 2.1-2.3, altering this policy will have a contemporaneous effect on outcomes as it alters the contemporaneous input decisions, which have been shown to directly affect outcomes. Additionally, there will be a dynamic effect on outcomes as lagged inputs and lagged outcomes affect contemporaneous input decisions which in turn affect outcomes. In figure 2.4, I show the results of this simulation, comparing math, reading, and non-cognitive skills in grades 1, 2 and 3, before and after the policy simulation where "old" denotes the average test scores under the existing policy regime and "new" denotes the average test scores under the proposed policy simulation.

Simulating through the model after changing the number of hours of school-related leave following the procedure outlined in Appendix section E.2.1 gives us point estimates of the new test scores and inputs. In order to get the corresponding standard errors on these points estimates to determine whether they are statistically significant, I use a bootstrap procedure. I briefly outline the procedure here and defer a more complete treatment to Appendix section E.2.1. The standard errors are obtained using a parametric bootstrap procedure with 1000 draws. In general, parametric bootstraps assume that the data come from a known distribution, in this case, a multi-variate normal distribution, with unknown mean and variance, that are here estimated using the full information maximum likelihood framework. Subsequent to recovering the mean and variance of the parameters, the bootstrap samples are constructed by parametrizing the assumed multi-variate normal distribution using the estimated mean and variance matrix. For each iteration of the simulation, new samples are drawn from this distribution, producing potentially different parameter estimates with each iteration. Subsequent to running all iterations, the standard errors are computed from the standard deviation of the estimates. Since all the estimates are statistically significant due to very precisely estimated standard errors ranging from 0.00004 to 0.00046, I suppress the standard errors and discuss the point estimates only.

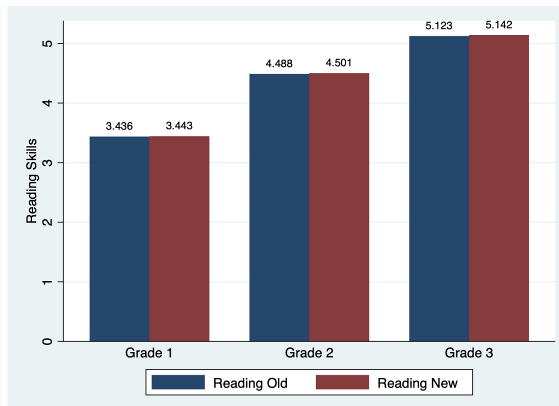
In figure 2.4, I show the result of this simulation where sub-figure 2.4(a) shows the change in math scores, sub-figure 2.4(b) shows the change in reading scores and sub-figure 2.4(c) shows the change in non-cognitive scores. As can be seen from the graphs, the change in math and reading scores is negligible across all grades, most less than half a percentage increase. However, looking at graph 2.4(c), we see larger effects in the effect of the policy change on non-cognitive skills, though only in grades 2 and 3, where the percentage changes are 3.28% and 4.96%, respectively. Having identified the effect of the policy simulation on the outcomes of interest, I now turn to identifying and quantifying the respective mechanisms through which the policy is affecting outcomes.

In figure 2.5, I show the effect of changing the policy on the three inputs that are directly affected by the policy: the probability of volunteering, the probability of attending a parent-teacher conference and the level of home inputs, where sub-figure 2.5(a) shows the effect on the probability of volunteering, sub-figure 2.5(b) shows the effect on attending a parent-teacher conference

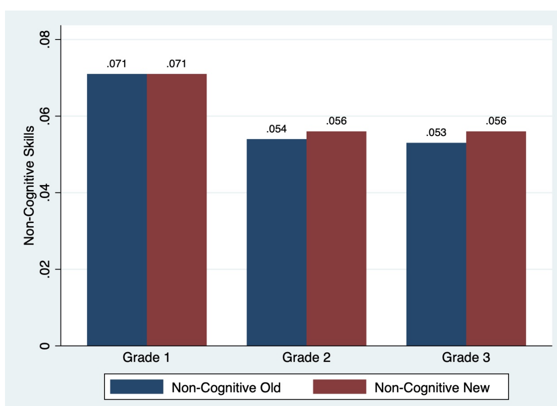
Figure 2.4: Three sub-figures showing average math, reading, and non-cognitive test scores before and after increasing the number of hours of school-related leave to 40 in all years: (a) shows math scores before and after the policy change; (b) shows reading scores before and after the policy change; (b) shows non-cognitive scores before and after the policy change.



(a) Average math scores before and after the policy change

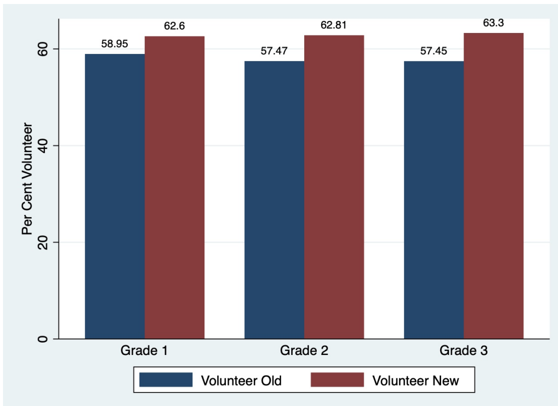


(b) Average reading scores before and after the policy change

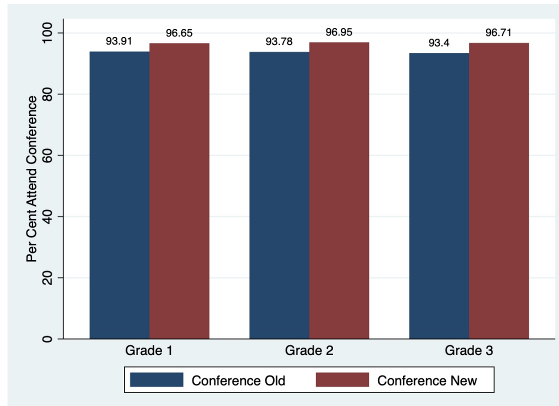


(c) Average non-cognitive scores before and after the policy change and sub-figure 2.5(c) shows the effect on the level of home inputs. As expected from analyzing the determinants of these input decisions, the policy has effects across all 3 inputs. For volunteering, the policy leads to a 3.7, 5.3, and 5.85 percentage point increase in grades 1, 2, and 3 respectively. For attending a parent-teacher conference the corresponding effect sizes are a 2.7, 3.2 and 3.3 percentage point increase in grades 1, 2, and 3 respectively. We also see changes in the level of home inputs of magnitude 0.06, 0.08 and 0.09 standard deviations in grades 1, 2, and 3, respectively. Though the home inputs do not directly affect non-cognitive skills, they still could indirectly affect them through the dependence of volunteering at school on prior home inputs, and the subsequent effect of volunteering at school on non-cognitive inputs. Despite the relatively large change in inputs, this does not translate into substantial changes in the math and reading test scores due to the relatively small effects of the inputs on these outcomes (See tables 2.1 and 2.2). Across all inputs, the increases are larger in the later grades, corresponding with a larger effect of the policy change on non-cognitive skills in these later grades. The larger increases in the inputs in the later grades, likely comes through the dynamic inter-dependence of these input decisions both through persistence as well as dynamic cross-effects. For instance, looking at the volunteering decision, we see that lagged volunteering, attending a parent-teacher conference and home inputs all positively and statistically significantly affect the probability of volunteering. Similarly, lagged volunteering, lagged conference, and to a lesser extent, lagged home inputs all affect the probability of attending a parent-teacher conference. The larger effects of the policies on non-cognitive skills in later grades could also be due to larger effects of volunteering in later grades as seen in table 2.9 and as is discussed in section 2.5.5.

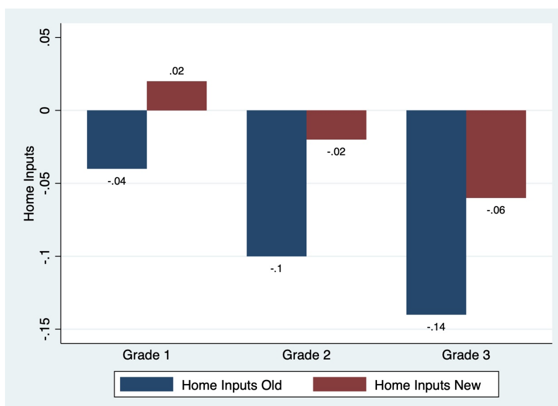
Figure 2.5: Three sub-figures showing the per cent volunteer, attend a parent-teacher conference, and average home inputs before and after increasing the number of hours of school-related leave to 40 in all years: (a) shows the per cent volunteering before and after the policy change; (b) shows the per cent attending a parent-teacher conference before and after the policy change; (c) shows average home inputs before and after the policy change.



(a) Per cent volunteer before and after the policy change



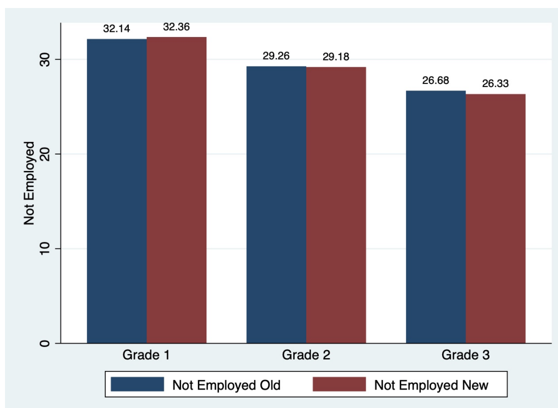
(b) Per cent attend parent-teacher conference before and after the policy change



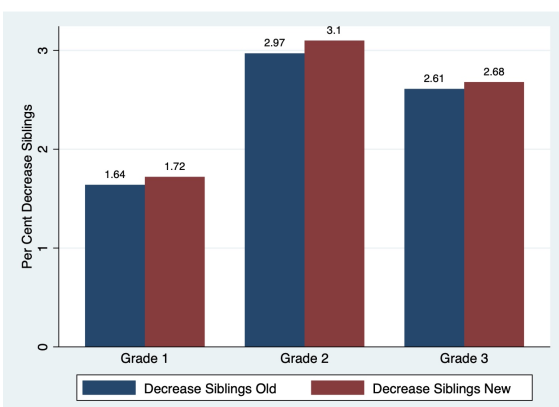
(c) Average home inputs before and after the policy change

In figure 2.6, I show the effect of the policy on the per cent of mothers not employed, the per cent of mothers that increase the number of siblings in the household and the per cent of mothers that decrease the number of siblings in the household. Is it important to bear in mind, that these inputs are not directly affected by the policy, so any changes in the inputs are coming though the dynamic interdependence of these input decisions on prior inputs and outcomes. Sub-figure 2.6(a) shows the effect on the probability of maternal non-employment, sub-figure 2.6(b) shows the effect on the proportion of mothers that decrease the number of siblings in the household and sub-figure 2.6(c) shows the effect on the proportion of mothers that increase the number of siblings in the household. As can be seen from the figures, the effects of the policies on these inputs are negligible with most changes being less than half a percentage point. The findings suggest that the indirect effects of the policy are extremely small in magnitude and are thus unlikely to be an important channel through which the policy impacts outcomes.

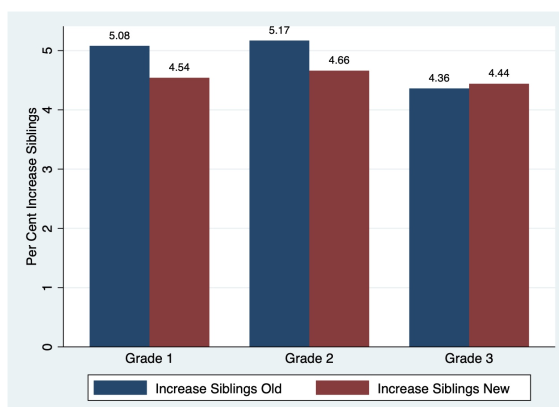
Figure 2.6: Three sub-figures showing the per cent not employed, decrease siblings, and increase siblings before and after increasing the number of hours of school-related leave to 40 in all years: (a) shows the per cent increase siblings before and after the policy change; (b) shows the per cent decrease siblings before and after the policy change; (c) shows the per cent increase siblings before and after the policy change.



(a) Per cent not employed before and after the policy change



(b) Per cent decrease siblings before and after the policy change



(c) Per cent increase siblings before and after the policy change

In summary, I find that altering the number of hours of school-related leave leads to an non-negligible increase in non-cognitive skills, primarily in the later grades. The primary mechanisms through which the policy is affecting outcomes seems to be through the direct effect of increasing the probability of volunteering, attending a parent-teacher conference, and to a lesser extent, increasing the level of inputs at home. I did not find substantial evidence of the policy affecting outcomes through indirect channels as the probability of the mother not being employed, the proportion of mothers that decrease siblings and the proportion of mothers that increased siblings largely remained unchanged.

2.7 Conclusion

Parental involvement has been promoted as a key component of education policy to improve child outcomes yet research on its causal effects is scarce. Much of the efforts to understand the effects of parental involvement have been hampered by the inability to adequately address non-random selection into parental involvement and account for the effects of related input decisions. One way to address this would be to rely on an instrumental variables approach to generate plausibly exogenous sources of variation, however a lack of good instruments has largely precluded this. By exploiting access to a rich dataset and exogenous variation in unique state labour policies aimed at increasing the level of parental involvement, as well as other state level policies, this paper is able to address this shortcoming and provide evidence of the causal effects of parental involvement.

Using an empirical model derived from economic theory, I find that volunteering at school has positive and similar effects for math, reading and non-cognitive skills and attending a parent-teacher conference has a weakly positive effect on math skills. When looking at the determinants of attending parent-teacher conferences, I find differences in the types of parents that engage in the two types of parental involvement with parents of children with lower prior cognitive and non-cognitive skills more likely to attend parent-teacher conferences. This stands in stark contrast to the finding that parents of children with higher prior cognitive and non-cognitive skills are more likely to volunteer at school. The two results seem to suggest that parents engage in different activities depending on their child's achievement whether through self-selection or at the behest of the child or teacher.

Using the estimated model, this paper provides the first evaluation of the effects of existing state-level policies that allow parents time off work to participate in their child's schooling aimed at addressing binding work commitments, the primary reason given for non-participation. Through model simulation using the framework of my empirical model, I find that allowing the maximum of 40 hours off leads to an increase in the accumulation of non-cognitive skills, particularly in the later grades. By exploiting the richness of the model, I am able to identify the primary mechanisms through which the policy operates as increases in the probability of the volunteering, increases in the probability of attending a parent-teacher conference and to a lesser extent, increases in the level of home inputs. I do not find much support for other indirect mechanisms such as changes in the maternal employment or fertility decisions.

In the context of the current policy climate with fourteen states currently having the policy in place and a further four states proposing bills to introduce this policy, and in the broader context of policy makers searching for innovative ways to get parents involved in their child's schooling, my research can inform the current policy debate as well as future policy debates going forward.

A.1 Appendix for Chapter 1

A.1.1 Tables and Figures

Table A.1.1: Mean and Standard Deviation of Select Child, Mother and Household Characteristics

	Grade 1	Grade 2	Grade 3
Child			
Male	50.38	50.78	50.76
White	54.45	54.67	56.54
Black	9.44	8.71	8.57
Hispanic	23.15	23.94	22.05
Other	12.96	12.68	12.84
Age	7.12	8.14	9.10
	(0.40)	(0.41)	(0.39)
Mother			
High School or Less	31.60	30.95	29.53
Some College	30.64	30.16	30.68
Bachelor's or Higher	37.67	38.52	39.72
Employed	67.75	70.93	73.68
Not Employed	32.25	29.07	26.32
Age	35.50	36.77	37.99
	(6.17)	(6.09)	(6.05)
Household			
Two parent	82.58	83.72	84.95
Single parent/Other	17.42	16.28	15.65
Household Income (000's)	72.89	76.31	82.17
	(55.92)	(57.30)	(57.76)
English	81.43	80.68	81.73
Non-English	18.57	19.32	18.18
Observations	8700	7500	5600

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard deviations for continuous variables are reported in parentheses. Standard deviations on discrete variables are suppressed for brevity.

Table A.1.2: Annual Hours of School-Related Leave by State

State	Annual Hours of Leave
California	40
District of Columbia	24
Massachusetts	24
Vermont	24
Colorado	18
Minnesota	16
Virginia	16
Rhode Island	10
Arkansas	8
Illinois	8
New Mexico	8
Texas	8
Nevada	4
North Carolina	4
Hawaii	2

Note: New York, New Jersey, Connecticut, and Michigan currently have pending bills.

Table A.1.3: Mean and Standard Deviation of Skills

	Grade 1	Grade 2	Grade 3
Math Scores	3.37	4.77	5.76
	(1.44)	(1.30)	(1.17)
Reading Scores	3.50	4.65	5.38
	(1.43)	(1.15)	(1.03)
Non-Cognitive Scores	0.26	-0.34	-0.30
	(0.96)	(0.87)	(0.86)
Approaches to Learning	0.06	0.06	0.09
	(0.06)	(0.06)	(0.09)
Self-Control	0.05	0.05	0.07
	(0.05)	(0.05)	(0.07)
Interpersonal Skills	0.05	0.06	0.07
	(0.05)	(0.06)	(0.07)
Externalizing Behaviour	0.04	0.05	0.05
	(0.04)	(0.05)	(0.05)
Internalizing Behaviour	0.03	0.04	0.05
	(0.03)	(0.04)	(0.05)
Attentional Focus	0.05	0.06	0.08
	(0.05)	(0.06)	(0.08)
Inhibitory Control	0.05	0.06	0.07
	(0.05)	(0.06)	(0.07)
Observations	8700	7500	5600

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard deviations are reported in parentheses.

Table A.1.4: Mean and Standard Deviation of Select Inputs

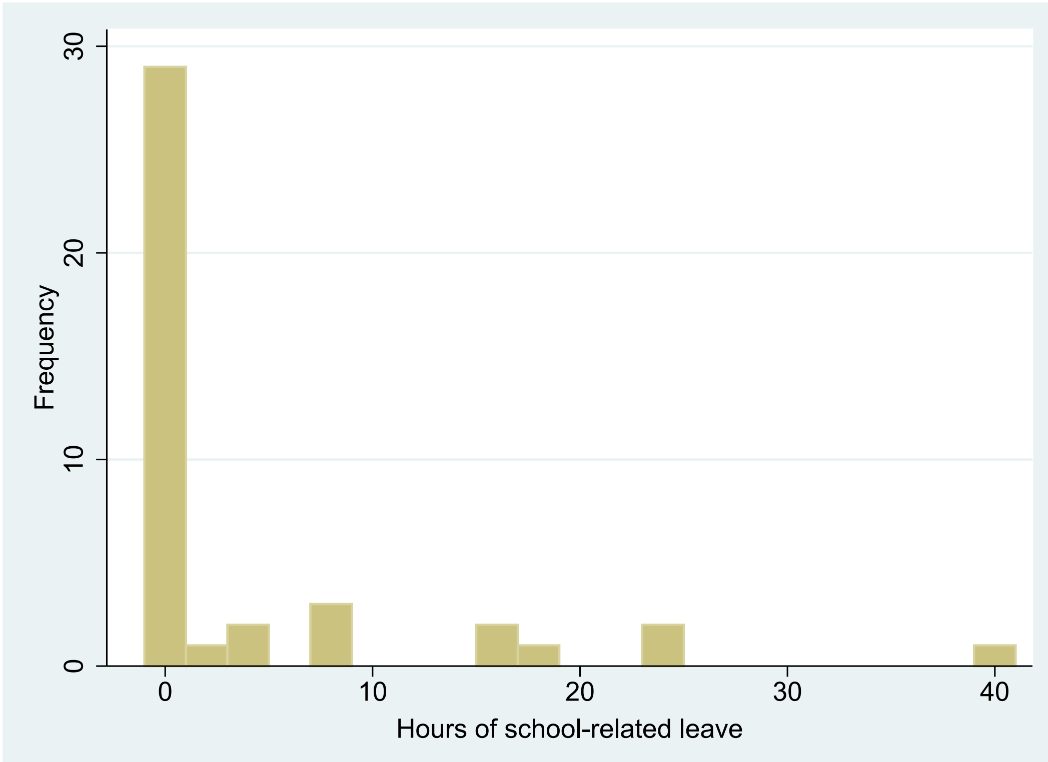
	Grade 1	Grade 2	Grade 3
Volunteer	59.62	56.74	56.88
Conference	93.92	92.76	92.06
Back to School Night	87.14	85.73	88.53
School Event	84.77	84.27	85.46
PTA/PTO Meetings	44.68	44.67	45.46
Maternal Employment	67.75	70.93	73.68
Home Inputs	-0.04	0.03	0.00
	(0.97)	(0.95)	(0.97)
Frequency Child Reads			
Never/Once or Twice a Week	21.79	18.14	18.79
Three to Six Times a Week	40.30	40.96	41.31
Everyday	37.91	40.90	39.90
Extra-Curricular Activities			
Child Participates	73.30	77.94	79.20
Hours of TV Watched			
Below Median Hours of TV	61.24	61.77	59.58
No. of Nights Eat Together			
Zero to Three	13.56	12.92	13.34
Four to Five	27.13	25.23	25.86
Six to Seven	59.31	61.85	60.80
Observations	8700	7500	5600

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard deviations for continuous variables are reported in parentheses. Standard deviations on discrete variables are suppressed for brevity.

Table A.1.5: State-Level Characteristics

	Grade 1	Grade 2	Grade 3
Expenditure per Pupil (000's)	10702.71	10803.00	11125.27
	(2854.82)	(2932.43)	(3072.52)
GDP per capita	45971.37	46165.81	46739.05
	(7600.28)	(7494.03)	(7611.58)
State Unemployment Rate	8.11	7.37	6.39
	(1.77)	(1.62)	(1.34)
Avg. Weekly Benefit	296.65	302.76	306.40
	(52.95)	(56.68)	(60.19)
Max. No. of Weeks of Welfare Benefits	25.51	25.32	24.83
	(1.98)	(2.18)	(3.12)
Avg. Unemployment Insurance Claims	5.71	5.19	4.07
	(1.13)	(1.10)	(0.87)

Figure A.1.7: Distribution of the Number of Hours of School-related Leave Entitlement Across States



B.1.1 Test of Equivalence of Means

The equivalence of means test is used to determine whether the means of two variables are close enough as to be considered equivalent, or stated differently, whether the difference between the two means is statistically indistinguishable from 0. The two variables here are the mean test scores for states that have the policy, μ^p and the mean test scores for states that do not have the policy, μ^{np}. I outline the test below.

1. I first formulate the null and alternative hypothesis for the difference in means using three t-tests:

Test	Null	Alternative	T-test
1	$\mu^{np} - \mu^p = 0$	$\mu^{np} - \mu^p \neq 0$	Two-tailed
2	$\mu^{np} - \mu^p \geq 0$	$\mu^{np} - \mu^p < 0$	One-tailed
3	$\mu^{np} - \mu^p \leq 0$	$\mu^{np} - \mu^p > 0$	One-tailed

2. Using the two samples, I calculate the standard error and degrees of freedom to construct the test statistic:

   Standard Error:

   $$SE = \left(\frac{s_{np}^2}{t_{np}} + \frac{s_p^2}{t_p} \right)^{\frac{1}{2}}$$

   where s_{np} is the standard deviation of the test scores in states without the policy, t_{np} is the number of states without the policy and s_p and t_p have analagous definitions for states with the policy.

   Degrees of Freedom:

   $$DF = \frac{\left(\frac{s_{np}^2}{t_{np}} + \frac{s_p^2}{t_p} \right)^2}{[(s_{np}^2/t_{np})^2/(t_{np} - 1)] + [(s_p^2/t_p)^2/(t_p - 1)]}$$

   Test Statistic:

   $$t = [(\bar{x}^{np} - \bar{x}^p]/SE$$

   where $\bar{x}^{np}$ is the sample mean for test scores in states without the policy and $\bar{x}^p$ is the sample mean for test scores in states with the policy.

3. I then compare the test statistic with the respective t critical value from the t Distribution corresponding to the degrees of freedom above and the chosen significance level.

A.2 Appendix for Chapter 2

A.2.1 Construction of Variables of Interest

Construction of Latent Factor for Non-Cognitive Skills

I use polychoric (Kolenikov and Angeles, 2004)[17] analysis to extract a latent factor for child non-cognitive skills. I outline the procedure used to extract the unobservable latent factor from the observed measures I have in my data below. There are assumed to be M^{A^n} measures for the latent factor of child non-cognitive achievement. The measurement system for the factor can be specified below as follows:

$$A^{n,m} = \alpha_0^{A^{n,m}} + \alpha_1^{A^{n,m}} A^n + \zeta_j^{A^{n,m}} \text{ for } m = 1, ..., M^{A^n} \tag{23}$$

where the term on the left hand side of the equation represents measure m of the associated latent factor, which is assumed to measure the underlying latent factor with some error. The coefficient on the latent factor $\alpha_1^{k,m}$ is the associated factor loading term which reflects how much the measure explains or "loads on" the latent factor.[18] $\zeta_{isj}^{k,m}$ is the error term in the measurement equation and $\alpha_0^{k,m}$ is a constant. The factor is identified under the assumption that all errors in the measurement equation are orthogonal to the latent factor and across measures.

Item Response Theory Test Scores

The measure of cognitive skills is constructed using Item Response Theory (IRT) math and reading scale scores. The main advantage of IRT scores over other measures of child cognitive skills such as raw test scores is that IRT adjusts for the probability of a low-ability child guessing a difficult question using the pattern of correct answers in combination with the difficulty of the correctly-answered questions. As such, it is likely to reduce the measurement error inherent in inferring ability from raw test scores. IRT scores also allow for comparability of scores across time even when the instruments used to determine ability differ across time. For ease of interpretation, the IRT math and reading scores are standardized relative to the Kindergarten test scores.[19]

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[17] Polychoric analysis to combine is a tool used to extract latent factors from any combination of binary, categorical, and continuous variables. Polychoric analysis assumes that ordinal and binary variables proxy for latent continuous variables that measure the latent factor of interest with noise and extract a factor based on the degree of correlation between the ordinal variables. The STATA routine, which estimates polychoric correlations, can be downloaded from http://www.unc.edu/∼ skolenik/strata/.

[18] For instance if the researcher observes 7 measures of non-cognitive skills, then m=1,2,3,4,5,6,7 in equation 1.

[19] For a more complete discussion on the use of IRT test scores in the ECLS-K see "User's Manual for the ECLS-K:2011 Kindergarten-Fourth Grade Data File and Electronic Codebook, Public Version" available at https://nces.ed.gov/pubs2018/2018032.pdf

B.2.1 State-Level Labor Market Conditions and Policies

State School-Leave Related Laws

In addition to the federal mandate of parental involvement set out as part of the 2001 No Child Left Behind Act, individual states have implemented legislation aimed at increasing the level of parental involvement in schools. One such policy is the provision of school-related leave whereby employed parents can take time off from their place of employment to participate in their child's schooling subject to employer verification and sufficient notice in advance. I exploit variation across states in the number of hours parents are allowed to take off per year, ranging from 2 hours in Hawaii to 40 hours in California. Whilst only two states provide paid leave, most states allow for parents to substitute other forms of paid leave for school-related leave. States also vary by whether the law applies to government employees or to all employees. Information on state school-related leave laws was gathered from state employment legislation.

State Labor Market Conditions

I use variation across states and time in variables aimed at capturing the local labour market conditions that define the environment in which the mother makes her labour force participation decisions. Specifically, I include the state per cent employed in services that could convey information about the demand for maternal labour. Information on state labour market conditions were collected from the American Community Survey 1-year estimates.

State Unemployment Insurance

Each state provides unemployment insurance designed to assist workers who become involuntarily separated from their jobs. Payouts are made from the Federal Unemployment Insurance Trust Fund, however, states have considerable discretion on how these payments are disbursed and the length of time the benefits are available. I use variation across states and time in the maximum number of weeks individuals can claim insurance benefits and the average unemployment insurance claim by adjusted gross income. Information on the length of unemployment insurance benefits were obtained from the U.S. Department of Labor and information on unemployment insurance claims were obtained from tax returns accessed through the Internal Revenue Service.

State Welfare Benefits

The Temporary Assistance for Needy Families (TANF) program provides temporary financial assistance for poor and vulnerable families. States have considerable discretion on how to implement the program. One dimension along which states have latitude is the weekly benefit for needy families. I use variation across states and time in the maximum weekly welfare benefit. Information on the maximum weekly benefit comes from Urban Institute's Welfare Rules Database.

State Child-Care Subsidies

Under the Child Care Development Fund (CCDF), states provide financial assistance to qualifying low-income families to allow them to be able to afford child care so they can participate in the labour force or further their education. Since states have discretion over the implementation, there is substantial variation across states in the program along four main dimensions: the maximum income in order to be eligible for subsidized child care, the average co-payment parents incur when accessing subsidized child care, minimum work hours requirements, and reimbursement amounts states pay to child-care providers. I use the state level expenditure on subsidized child care per child under the age of 6. In order to capture potential supply side constraints, I also consider the number of children per child care center. Information on state child care expenditures comes from the Office of Child Care, a subdivision of the U.S. Department of Health and Human Services. Information on the number of child care centers comes from the American Community Survey 1-year estimates.

State Child Tax Credits

Under the Child Tax Credit scheme, individuals with custody of dependent children under the age of 17 can get tax credits to defray the costs associated with raising children. The tax credit is designed to help individuals in low to mid income brackets and is thus not available to individuals above a certain income threshold. In 2010, the thresholds were $110,000 for married couples filing a joint return, $55,000 for married couples filing separate returns, and for all others, $75,000. I use state and time variation in the average child tax credit by adjusted gross income group claimed. Information on tax credits comes from tax returns accessed through the Internal Revenue Service.

Tax Rates

There is variation across states and time in the tax incidence of individuals according to state and federal tax rates that vary by income bracket, marital status, and the number of children in the household. Tax rates can affect the budget constraint of households and can thus affect input decisions. I use state and time variation in the average tax rates for families earning $25,000 filing jointly with 2 children. Information for average tax rates are obtained from the TAXSIM program housed at the National Bureau of Economic Research, which calculates federal and state income tax liabilities from household survey data.

Child Support Payments

Under Federal Law, non-custodial parents of divorced children are required to pay child support to the custodial parent for maintenance of the child until the child reaches the age of 18. Whilst mother to father transfers are possible, the vast majority of transfers are from fathers to mothers. There is substantial variation across states in how the rules are enforced in addition to the formulas used to compute the amount to be paid which affects child support disbursements. I use variation across state and time in the average child support payments per single female with children under 18. Child support payments can supplement maternal income of single women which may translate into increased child inputs. Information on child support distributions per state were gathered from the Office of Child Support Enforcement, a division of the Office of the Administration for Children and Families.

C.2.1 Likelihood Ratio Test

The Likelihood Ratio (LR) test is a test to evaluate the goodness of fit between two nested models. A more complex model, here the model with unobserved heterogeneity, is compared with a simpler model, here the model without unobserved heterogeneity, to estimate whether the more complex model fits the data better as evidenced by whether there is a statistically significant difference in the improvement of the value of the likelihood function. The form of the test statistic is the ratio of the two likelihood functions as follows:

$$LR = -2\Big(\frac{\mathcal{L}_c(\hat{\theta})}{\mathcal{L}_s(\hat{\theta})}\Big) \tag{24}$$

where $\mathcal{L}_c(\hat{\theta})$ is the value of the likelihood for the more complex model and $\mathcal{L}_s(\hat{\theta})$ is the value of the likelihood for the simpler model. The test statistic has a chi-squared asymptotic distribution with degrees of freedom equal to the difference in the number of parameters between the two models. The test statistic is compared with the relevant critical value to determine whether the difference is statistically significant. The variables used to construct the test statistic are outlined in the table below:

Table C.2.1: Comparison of the Value of the Likelihood Function Between the Heterogeneity and No Heterogeneity Models

Model	Likelihood	No. of Parameters
No Heterogeneity	-205457	422
Heterogeneity	-196992	517

The test statistic is χ^2=16930. The corresponding critical chi squared value with 95 degrees of freedom and a 99% significant level, $\chi^2_{0.01}(95)$, is 129.973. Based on a comparison between the test statistic and the respective critical value, it appears that there is a statistically significant improvement in the model with heterogeneity as compared with the model without unobserved heterogeneity.

D.2.1 Robustness Checks

School-Level unobserved heterogeneity

I model the school-level time-invariant unobserved heterogeneity using a correlated random effects specification using the Mundlak (1978) device which models the school-level permanent unobserved heterogeneity as a linear projection of the school time-average of the time-varying characteristics. The benefit of this approach is that it conserves on the estimation of additional parameters whilst accounting for the endogeneity of inputs with regards to school-level permanent unobserved factors in a manner similar to a school fixed effect model.[20] However, unlike a school fixed effect model, under certain assumptions consistent estimates of the variables that do not vary within a school can be recovered.[21] I use the parental involvement equation to illustrate the method. We can rewrite the original parental involvement equation including a school-level unobserved heterogeneity term, λ_s, as follows, where I decompose Z_{ist} into it's school time-varying and school non time-varying components as C_{st} and G_s, respectively:[22]

$$ln\Big(\frac{P(I_{ist}=0)}{P(I_{ist}=1)}\Big) = \delta_0^I A^c_{ist-1} + \delta_1^I A^n_{ist-1} + \delta_2^I I_{ist-1} + \delta_3^I H_{ist-1} + \delta_4^I E_{ist-1} + \delta_5^I K_{ist-1} + \delta_6^I X_{ist} + \delta_7^I C_{st} + \delta_8^I G_s + \lambda_s^I + \mu_{is}^I + \nu_{ist}^I + \epsilon_{ist}^I$$

The school-level permanent unobserved heterogeneity is modeled as a linear projection of the school level time-average of the time varying covariates in the parental involvement equation as follows and substituted into the parental involvement equation:[23]

$$\lambda_s = \sigma_0^I \bar{A}^c{}_{st-1} + \sigma_1^I \bar{A}^n{}_{st-1} + \sigma_2^I \bar{I}_{st-1} + \sigma_3^I \bar{H}_{st-1} + \sigma_4^I \bar{E}_{st-1} + \sigma_5^I \bar{K}_{st-1} + \sigma_6^I \bar{X}_{st-1} + \sigma_7^I \bar{C}_{st} + r_s$$

where the school level time-average of time-varying variables is assumed to be orthogonal to r_s by construction as r_s is assumed to be a true random effect. The school time-average of the time-varying characteristics are then substituted directly into the parental involvement input decision:

$$\begin{aligned} ln\Big(\frac{P(I_{ist}=0)}{P(I_{ist}=1)}\Big) = \delta_0^I A^I_{ist-1} + \delta_1^I A^n_{ist-1} + \delta_2^I I_{ist} + \delta_3^I H_{ist} + \delta_4^I E_{ist} + \delta_5^I K_{ist} + \\ \delta_6^I X_{ist} + \delta_7^I C_{st} + \delta_8^I G_s + \\ \sigma_0^I \bar{A}^I{}_{st-1} + \sigma_1^I \bar{A}^n{}_{st-1} + \sigma_2^I \bar{I}_{st-1} + \sigma_3^I \bar{H}_{st-1} + \sigma_4^I \bar{E}_{st-1} + \sigma_5^I \bar{K}_{st-1} + \\ \sigma_6^I \bar{X}_{ist} + \sigma_7^I \bar{C}_{st} + \\ r_s + \mu_{is}^c + \nu_{ist}^c + \epsilon_{ist}^c \end{aligned}$$

---

[20] In fact the parameters on the time-varying variables at the school level will be the same as the ones estimated in a school fixed effect model (Mundlak, 1978).

[21] This is not possible in a fixed effect model as these time-invariant terms would be removed through differencing or demeaning.

[22] I drop the i subscript from these variables as they are constant for individuals within the same school.

[23] I retain the time superscript on the lagged terms to minimize confusion with the notation.

The coefficients of interest can be recovered by estimating the equation by ordinary least squares. A Hausman test of zero correlation between the covariates and the school-level unobserved heterogeneity is given by a joint test:

$$H_0 : \sigma_0 = \sigma_1 = ... = \sigma_6 = 0$$
H_a: At least one σ is non-zero

Under very strict exogeneity conditions, the coefficients on the school non time-varying components, δ_8^I can be recovered.

E.2.1 Simulation Procedure

Simulations

Subsequent to estimating the model using full information maximum likelihood, I use simulations to quantify effect sizes of interest. I use the technique both to determine the long-term effects of volunteering and attending a parent-teacher, as well as to determine the effects of the policy simulation. The simulation procedure is outlined as follows:

1. I use the estimated coefficients, mass points and probability weights to simulate the model to predict the set of input decisions for each individual in the sample: volunteering, attending a parent-teacher conference, home inputs, maternal employment, and fertility decisions. In order to generate an idiosyncratic error term, I followed the procedure below:

   a. For discrete variables, I compared the predicted probabilities to a random draw from a uniform distribution with endpoints zero and one. If the predicted probability was greater than the random draw, I would assign a 1 to that variable and a 0 otherwise.

   b. For continuous variables, I generated a draw from a uniform random distribution with endpoints zero and 1, multiplied by the standard deviation of the continuous variable, and added this random variable to the predicted values.

2. I then predicted the outcome equations: math skills, reading skills and non-cognitive skills by replacing the actual input decisions with their predicted values based on step 1 above. I followed the same procedure outlined above to generate an idiosyncratic error term and added it to the predicted values.

3. The predicted input decisions and outcome equations estimated in steps 1 and 2 above, are then used as the next period's lags.

   a. I update the number of siblings going into period $t + 1$ by adjusting the number of siblings entering period t by the respective maternal fertility decision based on whether it is predicted that she increases, decreases or keeps the number of siblings the same.

4. The process is repeated for each period until the terminal period of data.

Parametric Bootstrapped Standard Errors

The procedure above gives the point estimates of the effect sizes of interest, in order to get the corresponding standard errors for these estimates, I use a parametric bootstrap procedure. The parametric bootstrap procedure is outlined below:

1. I assume that the entire set of estimated coefficients, mass points, and probability weights follow a multivariate normal distribution with mean corresponding to the point estimates of the parameters and the covariance matrix corresponding the estimated covariance matrix for the set of parameters.

2. I then draw a set of normally distributed random variables from this distribution and perturb each estimated coefficient using this random variable.

3. I simulate through the model using the procedure outlined in section E.2.1 using the perturbed coefficients to get predicted variables for my parameters of interest.

4. I repeat the process 1000 times and save the estimated coefficients.

5. I construct the standard deviation based on the 1000 estimated coefficients.

6. I construct the standard errors from the standard deviation.

F.2.1 Tables

Table F.2.1: Statistics for Attrition over the Waves for the Full Sample

Measure	Wave				
	Kgn. Fall	Kgn. Spring	Grade 1	Grade 2	Grade 3
Number	18,200	17,800	16,000	14,800	14,000
Per cent attrition (Over initial wave)	-	2.20%	12.09%	18.68%	23.08%
Per cent attrition (Over previous wave)	-	2.20%	10.11%	7.5%	5.41%

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset.

Table F.2.2: Select Mother, Child and Household Characteristics

Variable	Spring-Kgn		Spring-1st		Spring-2nd Grade		Spring-3rd Grade	
	Original	Restricted	Original	Restricted	Original	Restricted	Original	Restricted
Child								
Male	51.20	51.02	51.22	50.38	51.11	50.78	51.27	50.76
White	46.81	57.86	46.97	54.45	47.44	54.67	47.59	56.54
Black	13.07	10.02	12.14	9.44	11.46	8.71	11.04	8.57
Hispanic	25.43	19.54	26.12	23.15	26.67	23.94	26.98	22.05
Other	14.68	12.59	14.47	12.96	14.43	12.68	14.39	12.84
Age	6.13	6.12	7.13	7.12	8.15	8.14	9.12	9.10
	(0.42)	(0.41)	(0.42)	(0.40)	(0.43)	(0.41)	(0.42)	(0.39)
Mother								
High School or Less	32.45	27.09	33.44	31.60	33.60	30.95	33.60	29.53
Some College	28.60	32.41	28.63	30.64	28.54	30.16	28.54	30.68
Bachelor's or Higher	29.17	40.50	30.13	37.67	30.49	38.52	30.49	39.72
Employed	63.14	64.32	65.57	67.75	68.84	70.93	71.46	73.68
Age	34.25	34.37	35.28	35.50	36.35	36.77	37.49	37.99
	(6.27)	(6.19)	(6.24)	(6.17)	(6.22)	(6.09)	(6.24)	(6.05)
Household								
Two parent	77.63	82.72	77.39	82.58	77.37	83.72	77.71	84.95
Single parent/Other	22.37	17.28	22.61	17.42	22.63	16.28	22.29	15.65
Siblings	1.50	1.53	1.55	1.56	1.58	1.59	1.60	1.61
	(1.12)	(1.11)	(1.13)	(1.11)	(1.13)	(1.09)	(1.13)	(1.08)
Household Income (000's)	67.34	74.28	68.59	72.89	70.39	76.31	75.30	82.17
	(54.55)	(55.48)	(55.75)	(55.92)	(56.79)	(57.30)	(57.83)	(57.76)
English	79.90	86.49	78.91	81.43	78.56	80.68	78.27	81.73
Non-English	20.10	13.49	21.09	18.57	21.44	19.32	21.73	18.18
Observations	16500	8550	15100	8700	14050	7500	13300	5600

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Categories may not sum to 100 due to the omission of the missing categories. Standard deviations for continuous variables are reported in parentheses. Standard deviations on discrete variables are suppressed for brevity.

Table F.2.3: Child Outcome Variables

Variable	Spring-Kgn		Spring-1st Grade		Spring-2nd Grade		Spring-3rd Grade	
	Original	Restricted	Original	Restricted	Original	Restricted	Original	Restricted
Math Scores	1.19	1.36	3.19	3.37	4.58	4.77	5.55	5.76
	(1.08)	(1.07)	(1.45)	(1.44)	(1.37)	(1.30)	(1.25)	(1.17)
Reading Scores	1.24	1.41	3.33	3.50	4.49	4.65	5.20	5.38
	(1.19)	(1.19)	(1.46)	(1.43)	(1.21)	(1.15)	(1.11)	(1.03)
Non-Cognitive Scores	0.26	0.33	0.23	0.26	-0.36	-0.34	-0.34	-0.30
	(1.03)	(0.99)	(0.98)	(0.96)	(0.89)	(0.87)	(0.88)	(0.86)
Observations	16500	8550	15100	8700	14050	7500	13300	5600

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard deviations for continuous variables are reported in parentheses. Standard deviations on discrete variables are suppressed for brevity.

Table F.2.4: Child Input Variables

Variable	Spring-Kgn		Spring-1st Grade		Spring-2nd Grade		Spring-3rd Grade	
	Original	Restricted	Original	Restricted	Original	Restricted	Original	Restricted
Mother Not Employed	36.86	35.68	34.43	32.25	31.16	29.07	28.54	26.32
Volunteer	57.62	62.67	56.22	59.62	52.92	56.74	51.83	56.88
Conference	90.51	91.68	93.55	93.92	92.80	92.76	92.04	92.06
Decrease Siblings	-	-	1.52	1.68	2.36	2.59	2.19	2.37
Increase Siblings	-	-	4.18	5.06	4.19	4.91	3.59	4.09
Home Inputs	-0.04	-0.00	-0.04	-0.04	0.06	0.03	0.03	0.00
	(1.00)	(0.93)	(1.00)	(0.97)	(0.99)	(0.95)	(1.00)	(0.97)
Frequency Child Reads								
Never/Once or Twice a Week	22.51	19.56	23.26	21.79	19.50	18.14	20.44	18.79
Three to Six Times a Week	33.44	35.53	38.53	40.30	39.96	40.96	39.44	41.31
Everyday	44.05	44.91	38.21	37.91	40.53	40.90	40.13	39.90
Extra-Curricular Activities								
Child Participates	62.25	67.77	70.14	73.30	74.39	77.94	75.26	79.20
Hours of TV Watched								
Below Median Hours of TV	47.63	50.63	60.07	61.24	60.58	61.77	58.61	59.58
No. of Nights Eat Together								
Zero to Three	11.15	9.87	14.02	13.56	12.99	12.92	13.52	13.34
Four to Five	25.80	27.58	25.97	27.13	23.70	25.23	24.75	25.86
Six to Seven	63.05	62.55	60.01	59.31	63.31	61.85	61.73	60.80
Observations	16500	8550	15100	8700	14050	7500	13300	5600

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard deviations for continuous variables are reported in parentheses. Standard deviations on discrete variables are suppressed for brevity.

Table F.2.5: Variables and Their Associated Factor Loadings for Non-cognitive Skills

Variable	Factor Loading
Approaches to Learning	0.86
Self-Control	0.82
Inter-personal Skills	0.80
Internalizing Behaviour	0.37
Externalizing Behaviour	0.75
Inhibitory Control	0.81
Attentional Focus	0.78

Table F.2.6: Summary Statistics of Initial Exclusion Restrictions

Variable	Mean
Continuous	
Mother's age at first birth	25.07
	(5.76)
Child's birth weight (pounds)	7.13
	(1.30)
No. of older siblings	0.88
	(0.98)
Birth order	1.57
	(0.70)
Discrete	
Mother not married at time of birth	27.04
Observations	8550

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard deviations for continuous variables are reported in parentheses. Standard deviations on discrete variables are suppressed for brevity.

Table F.2.7: Means and Standard Deviations of State-Level Exogenous Variables

Variable	2011	2012	2013	2014
State Hours of School-Related Leave per Year	7.12	7.79	8.13	8.08
	(12.58)	(13.21)	(13.44)	(13.43)
State Average Tax Liability for a Family earning $25,000	-0.19	-0.20	-0.24	-0.28
	(0.60)	(0.61)	(0.64)	(0.72)
State Max No. of Weeks of Unemployment Insurance	25.76	25.40	25.16	24.28
	(1.37)	(1.88)	(2.08)	(3.36)
State Average Child Tax Credit (000's)	1.09	1.11	1.11	1.15
	(0.54)	(0.50)	(0.50)	(0.49)
State Average Unemployment Insurance Claim (000's)	6.55	6.02	5.59	4.41
	(1.34)	(1.20)	(1.17)	(1.00)
State Expenditure on Subsidized Child Care (000,000's)	4.11	4.04	4.17	4.53
	(1.21)	(1.21)	(1.30)	(1.42)
State Children per Child Care Center	138.21	160.61	163.89	154.21
	(70.61)	(81.87)	(90.11)	(89.02)
State Maximum Weekly Benefit	431.79	438.77	438.44	441.68
	(106.01)	(111.46)	(115.10)	(122.57)
State Avg. Child Support (000,000's)	2.64	2.66	2.71	2.78
	(0.88)	(0.90)	(0.93)	(0.94)
State Per Cent Employed in Services	17.45	17.81	18.08	18.11
	(1.58)	(1.62)	(1.65)	(1.63)
Observations	8550	8700	7500	5600

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard deviations are reported in parentheses.

Table F.2.8: Logit: Approximation to the Volunteering Decision

	(1) OLS		(2) FIML	
Lag Reading Score	0.0306**	(0.0145)	0.0659***	(0.0213)
Lag Non-Cognitive Score	0.0620***	(0.0193)	0.0668***	(0.0198)
Lag Mother Not Employed	0.3195***	(0.0407)	0.3190***	(0.0407)
Lag Volunteering	2.0273***	(0.0368)	2.0279***	(0.0416)
Lag Conference	0.3116***	(0.0711)	0.3273***	(0.0717)
Lag Home Inputs	0.1114***	(0.0193)	0.0755***	(0.0214)
Lag No. of Siblings	−0.0189	(0.0168)	−0.0171	(0.0167)
Female	0.0523	(0.0342)	0.0494	(0.0346)
Mother's Age	0.2333	(0.1532)	0.2272	(0.1654)
Mother's Age Sq.	−0.0136	(0.0205)	−0.0129	(0.0222)
Some College	0.2156***	(0.0447)	0.2084***	(0.0448)
Bachelors or Higher	0.4979***	(0.0507)	0.4841***	(0.0528)
Household Income	0.4232***	(0.0446)	0.4297***	(0.0454)
Black	−0.1760***	(0.0632)	−0.1602**	(0.0643)
Hispanic	−0.1505***	(0.0559)	−0.1408**	(0.0567)
Other	−0.3504***	(0.0617)	−0.3393***	(0.0619)
Single Parent	0.0784	(0.0508)	0.0765	(0.0508)
Non-English Home Language	−0.2683***	(0.0573)	−0.2679***	(0.0584)
Hours of School-Related Leave	0.0058***	(0.0015)	0.0060***	(0.0016)
Avg. Unemployment Insurance Tax	−0.0245	(0.0251)	−0.0248	(0.0247)
Children per Child Care Center	0.0007***	(0.0002)	0.0007***	(0.0002)
Maximum Weekly Benefit	−0.0002	(0.0003)	−0.0003	(0.0003)
Avg. Child Support (000's)	−0.0042	(0.0226)	−0.0026	(0.0228)
Per Cent Employed in Services	−0.0030	(0.0110)	−0.0034	(0.0116)
Subsidized Child Care Expenditure (000's)	0.0345**	(0.0160)	0.0370**	(0.0161)
Avg. Child Tax Credit	0.2245***	(0.0452)	0.2263***	(0.0450)
Average Tax Liability for a Family earning $25,000	0.1202***	(0.0318)	0.1207***	(0.0317)
Grade 2	−0.2668***	(0.0509)	−0.3188***	(0.0604)
Grade 3	−0.3315***	(0.0774)	−0.4215***	(0.0891)
Constant	−2.5550***	(0.3726)	−2.6263***	(0.3986)
Mother/Child Type 1			−0.1488	(0.1113)
Mother/Child Type 2			0.0653	(0.0768)
Mother/Child Type 3			−0.3593***	(0.1096)
Time-Varying Type 1			0.2656*	(0.1421)
Time-Varying Type 2			0.2982**	(0.1321)
Observations	21750		21750	

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors are reported in parentheses. Missing data indicators are suppressed for brevity.

Table F.2.9: Logit: Approximation to the Conference Decision

	(1) OLS		(2) FIML	
Lag Reading Score	-0.0902^{***}	(0.0265)	-0.0936^{**}	(0.0374)
Lag Non-Cognitive Score	-0.1261^{***}	(0.0357)	-0.1196^{***}	(0.0361)
Lag Mother Not Employed	0.0794	(0.0704)	0.0790	(0.0713)
Lag Volunteering	0.5563^{***}	(0.0670)	0.5495^{***}	(0.0682)
Lag Conference	2.0292^{***}	(0.0724)	2.0398^{***}	(0.0827)
Lag Home Inputs	0.0520	(0.0324)	0.0205	(0.0362)
Lag No. of Siblings	0.0072	(0.0284)	0.0051	(0.0278)
Female	-0.1777^{***}	(0.0607)	-0.1774^{***}	(0.0615)
Mother's Age	0.0318	(0.2644)	0.0305	(0.2389)
Mother's Age Sq.	0.0064	(0.0352)	0.0070	(0.0314)
Some College	0.1807^{**}	(0.0753)	0.1850^{**}	(0.0741)
Bachelors or Higher	0.5710^{***}	(0.0966)	0.5776^{***}	(0.1009)
Household Income	0.2244^{**}	(0.0875)	0.2322^{***}	(0.0881)
Black	0.3071^{***}	(0.1075)	0.3153^{***}	(0.1017)
Hispanic	-0.0467	(0.0970)	-0.0473	(0.0953)
Other	0.2982^{**}	(0.1295)	0.3161^{**}	(0.1350)
Single Parent	-0.0721	(0.0834)	-0.0756	(0.0818)
Non-English Home Language	0.1220	(0.1037)	0.1211	(0.1005)
Hours of School-Related Leave	0.0187^{***}	(0.0035)	0.0187^{***}	(0.0034)
Avg. Unemployment Insurance Tax	-0.2082^{***}	(0.0496)	-0.2113^{***}	(0.0510)
Children per Child Care Center	-0.0007^{*}	(0.0004)	-0.0007^{*}	(0.0004)
Maximum Weekly Benefit	0.0033^{***}	(0.0006)	0.0034^{***}	(0.0006)
Avg. Child Support (000's)	-0.2097^{***}	(0.0376)	-0.2118^{***}	(0.0374)
Per Cent Employed in Services	0.1041^{***}	(0.0208)	0.1048^{***}	(0.0213)
Subsidized Child Care Expenditure (000's)	0.3132^{***}	(0.0391)	0.3139^{***}	(0.0385)
Avg. Child Tax Credit	0.3001^{***}	(0.0784)	0.3079^{***}	(0.0763)
Average Tax Liability for a Family earning $25,000	-0.4433^{***}	(0.0813)	-0.4471^{***}	(0.0873)
Grade 2	-0.2925^{***}	(0.0945)	-0.2601^{**}	(0.1067)
Grade 3	-0.6129^{***}	(0.1452)	-0.5755^{***}	(0.1623)
Constant	-2.3228^{***}	(0.6536)	-2.3950^{***}	(0.6442)
Mother/Child Type 1			0.0085	(0.1921)
Mother/Child Type 2			0.0517	(0.1286)
Mother/Child Type 3			-0.2987	(0.1838)
Time-Varying Type 1			-0.4830^{**}	(0.2341)
Time-Varying Type 2			0.3190	(0.2435)
Observations	21750		21750	

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors are reported in parentheses. Missing data indicators are suppressed for brevity.

Table F.2.10: Continuous: Approximation to the Home Input Decisions

	(1) OLS		(2) FIML	
Lag Reading Score	0.0358^{***}	(0.0050)	0.0319^{***}	(0.0083)
Lag Non-Cognitive Score	0.0004	(0.0064)	0.0006	(0.0074)
Lag Mother Not Employed	0.0522^{***}	(0.0130)	0.0465^{***}	(0.0142)
Lag Volunteering	0.0862^{***}	(0.0132)	0.0654^{***}	(0.0139)
Lag Conference	0.0367	(0.0258)	0.0587^{**}	(0.0263)
Lag Home Inputs	0.3987^{***}	(0.0083)	0.2881^{***}	(0.0117)
Lag No. of Siblings	0.0012	(0.0056)	0.0010	(0.0062)
Female	0.0370^{***}	(0.0114)	0.0424^{***}	(0.0125)
Mother's Age	-0.0519	(0.0479)	-0.0493	(0.0510)
Mother's Age Sq.	0.0020	(0.0065)	0.0024	(0.0069)
Some College	0.0718^{***}	(0.0164)	0.0763^{***}	(0.0177)
Bachelors or Higher	0.1556^{***}	(0.0180)	0.1667^{***}	(0.0199)
Household Income	0.0388^{***}	(0.0140)	0.0477^{***}	(0.0147)
Black	-0.1790^{***}	(0.0246)	-0.1726^{***}	(0.0267)
Hispanic	-0.1459^{***}	(0.0205)	-0.1525^{***}	(0.0221)
Other	0.0021	(0.0229)	0.0223	(0.0228)
Single Parent	0.0697^{***}	(0.0187)	0.0706^{***}	(0.0196)
Non-English Home Language	0.0489^{**}	(0.0220)	0.0565^{**}	(0.0225)
Hours of School-Related Leave	0.0019^{***}	(0.0005)	0.0018^{***}	(0.0005)
Avg. Unemployment Insurance Tax	-0.0359^{***}	(0.0084)	-0.0362^{***}	(0.0085)
Children per Child Care Center	0.0002^{***}	(0.0001)	0.0002^{**}	(0.0001)
Maximum Weekly Benefit	0.0005^{***}	(0.0001)	0.0005^{***}	(0.0001)
Avg. Child Support (000's)	-0.0192^{**}	(0.0075)	-0.0159^{**}	(0.0080)
Per Cent Employed in Services	0.0127^{***}	(0.0037)	0.0135^{***}	(0.0040)
Subsidized Child Care Expenditure (000's)	0.0075	(0.0053)	0.0100^{*}	(0.0055)
Avg. Child Tax Credit	0.0121	(0.0152)	0.0141	(0.0160)
Average Tax Liability for a Family earning $25,000	-0.0136	(0.0098)	-0.0123	(0.0104)
Grade 2	-0.1364^{***}	(0.0174)	-0.1305^{***}	(0.0208)
Grade 3	-0.2398^{***}	(0.0256)	-0.2354^{***}	(0.0312)
Constant	-0.4932^{***}	(0.1210)	-0.5510^{***}	(0.1319)
Mother/Child Type 1			0.0701	(0.0460)
Mother/Child Type 2			0.1041^{***}	(0.0332)
Mother/Child Type 3			-1.0747^{***}	(0.0582)
Time-Varying Type 1			0.0380	(0.0567)
Time-Varying Type 2			-0.0312	(0.0589)
Observations	21750		21750	

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors are reported in parentheses. Missing data indicators are suppressed for brevity.

Table F.2.11: Logit: Approximation to the Maternal Non-Employment Decision

	(1) OLS		(2) FIML	
Lag Reading Score	−0.0153	(0.0169)	−0.0155	(0.0251)
Lag Non-Cognitive Score	−0.0174	(0.0234)	−0.0182	(0.0238)
Lag Mother Not Employed	3.3031***	(0.0444)	3.3041***	(0.0488)
Lag Volunteering	0.2073***	(0.0512)	0.2036***	(0.0514)
Lag Conference	−0.2311***	(0.0887)	−0.2241**	(0.0890)
Lag Home Inputs	0.0243	(0.0242)	−0.0035	(0.0272)
Lag No. of Siblings	0.1520***	(0.0204)	0.1519***	(0.0207)
Female	0.0284	(0.0407)	0.0317	(0.0409)
Mother's Age	−0.6284***	(0.1789)	−0.6309***	(0.1788)
Mother's Age Sq.	0.0883***	(0.0238)	0.0888***	(0.0240)
Some College	−0.2422***	(0.0555)	−0.2416***	(0.0541)
Bachelors or Higher	−0.5095***	(0.0623)	−0.5085***	(0.0634)
Household Income	0.0370	(0.0515)	0.0385	(0.0520)
Black	−0.1964**	(0.0818)	−0.1944**	(0.0791)
Hispanic	−0.0144	(0.0677)	−0.0173	(0.0671)
Other	−0.0667	(0.0723)	−0.0650	(0.0741)
Single Parent	0.5574***	(0.0649)	0.5575***	(0.0636)
Non-English Home Language	0.1896***	(0.0687)	0.1925***	(0.0672)
Hours of School-Related Leave	−0.0005	(0.0018)	−0.0005	(0.0018)
Avg. Unemployment Insurance Tax	0.0684**	(0.0297)	0.0690**	(0.0296)
Children per Child Care Center	0.0014***	(0.0002)	0.0014***	(0.0002)
Maximum Weekly Benefit	−0.0007**	(0.0003)	−0.0007**	(0.0003)
Avg. Child Support (000's)	0.0092	(0.0277)	0.0097	(0.0275)
Per Cent Employed in Services	−0.0290**	(0.0143)	−0.0291**	(0.0130)
Subsidized Child Care Expenditure (000's)	0.0340*	(0.0196)	0.0341*	(0.0195)
Avg. Child Tax Credit	−0.5996***	(0.0533)	−0.5989***	(0.0534)
Average Tax Liability for a Family earning $25,000	0.2102***	(0.0389)	0.2101***	(0.0393)
Grade 2	−0.1550***	(0.0588)	−0.1510**	(0.0690)
Grade 3	−0.0761	(0.0925)	−0.0722	(0.1064)
Constant	−0.7898*	(0.4558)	−0.7972*	(0.4450)
Mother/Child Type 1			0.0427	(0.1316)
Mother/Child Type 2			0.0022	(0.0927)
Mother/Child Type 3			−0.3074**	(0.1434)
Time-Varying Type 1			0.0880	(0.1525)
Time-Varying Type 2			0.0526	(0.1269)
Observations	21750		21750	

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors are reported in parentheses. Missing data indicators are suppressed for brevity.

Table F.2.12: Logit: Approximation to the Decrease Siblings Decision

	(1) OLS		(2) FIML	
Lag Reading Score	−0.0512	(0.0454)	−0.0682	(0.0726)
Lag Non-Cognitive Score	−0.1506***	(0.0549)	−0.1524***	(0.0585)
Lag Mother Not Employed	−0.1605	(0.1117)	−0.1648	(0.1171)
Lag Volunteering	−0.2280**	(0.1130)	−0.2106*	(0.1180)
Lag Conference	−0.2980*	(0.1776)	−0.3021*	(0.1809)
Lag Home Inputs	−0.0876*	(0.0527)	−0.0505	(0.0667)
Lag No. of Siblings	0.5747***	(0.0339)	0.5764***	(0.0401)
Female	0.2859***	(0.1029)	0.2971***	(0.1105)
Mother's Age	3.7350***	(0.8755)	3.6918***	(0.9055)
Mother's Age Sq.	−0.3101***	(0.0994)	−0.3049***	(0.1034)
Some College	0.0292	(0.1395)	0.0402	(0.1446)
Bachelors or Higher	−0.7231***	(0.1692)	−0.7086***	(0.1783)
Household Income	−0.1764	(0.1313)	−0.1819	(0.1345)
Black	0.1527	(0.1778)	0.1499	(0.1836)
Hispanic	−0.2549	(0.1720)	−0.2646	(0.1854)
Other	−0.3677	(0.2269)	−0.3876*	(0.2337)
Single Parent	−0.2487	(0.1518)	−0.2499*	(0.1507)
Non-English Home Language	−0.6257***	(0.1980)	−0.6138***	(0.2148)
Hours of School-Related Leave	0.0022	(0.0050)	0.0022	(0.0053)
Avg. Unemployment Insurance Tax	0.0320	(0.0709)	0.0333	(0.0716)
Children per Child Care Center	0.0009*	(0.0006)	0.0009	(0.0006)
Maximum Weekly Benefit	−0.0004	(0.0008)	−0.0004	(0.0008)
Avg. Child Support (000's)	0.1328*	(0.0729)	0.1349*	(0.0769)
Per Cent Employed in Services	0.0472	(0.0313)	0.0484	(0.0344)
Subsidized Child Care Expenditure (000's)	0.0124	(0.0539)	0.0116	(0.0549)
Avg. Child Tax Credit	−0.3264**	(0.1329)	−0.3206**	(0.1372)
Average Tax Liability for a Family earning $25,000	0.1607*	(0.0958)	0.1562	(0.0982)
Grade 2	0.3504**	(0.1492)	0.4042**	(0.1761)
Grade 3	0.1962	(0.2371)	0.2711	(0.2811)
Constant	−14.8067***	(1.9327)	−14.7733***	(2.0170)
Mother/Child Type 1			0.1445	(0.3799)
Mother/Child Type 2			−0.1009	(0.2637)
Mother/Child Type 3			0.2862	(0.3507)
Time-Varying Type 1			−1.3292	(2.8987)
Time-Varying Type 2			0.2483	(0.2751)
Observations	21750		21750	

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors are reported in parentheses. Missing data indicators are suppressed for brevity.

Table F.2.13: Logit: Approximation to the Increase Siblings Decision

	(1) OLS		(2) FIML	
Lag Reading Score	-0.0115	(0.0298)	-0.0533	(0.0448)
Lag Non-Cognitive Score	-0.0707^{*}	(0.0365)	-0.0775^{**}	(0.0376)
Lag Mother Not Employed	0.1080	(0.0710)	0.1069	(0.0702)
Lag Volunteering	0.0506	(0.0719)	0.0525	(0.0718)
Lag Conference	-0.1337	(0.1144)	-0.1373	(0.1169)
Lag Home Inputs	0.0178	(0.0350)	0.0203	(0.0396)
Lag No. of Siblings	-0.2044^{***}	(0.0459)	-0.2058^{***}	(0.0455)
Female	-0.0049	(0.0670)	0.0028	(0.0675)
Mother's Age	0.1019	(0.2299)	0.0940	(0.2586)
Mother's Age Sq.	-0.1117^{***}	(0.0383)	-0.1101^{***}	(0.0418)
Some College	-0.1565^{*}	(0.0840)	-0.1457^{*}	(0.0843)
Bachelors or Higher	-0.2727^{***}	(0.1027)	-0.2485^{**}	(0.1054)
Household Income	-0.2214^{**}	(0.0975)	-0.2234^{**}	(0.0974)
Black	0.2696^{**}	(0.1269)	0.2538^{**}	(0.1252)
Hispanic	0.1092	(0.1139)	0.0961	(0.1131)
Other	-0.0767	(0.1348)	-0.0822	(0.1321)
Single Parent	0.5714^{***}	(0.1093)	0.5783^{***}	(0.1090)
Non-English Home Language	0.1456	(0.1189)	0.1460	(0.1175)
Hours of School-Related Leave	-0.0031	(0.0031)	-0.0033	(0.0030)
Avg. Unemployment Insurance Tax	0.0124	(0.0467)	0.0128	(0.0466)
Children per Child Care Center	0.0015^{***}	(0.0004)	0.0015^{***}	(0.0004)
Maximum Weekly Benefit	0.0000	(0.0005)	0.0000	(0.0005)
Avg. Child Support (000's)	-0.0096	(0.0450)	-0.0123	(0.0447)
Per Cent Employed in Services	-0.0094	(0.0213)	-0.0100	(0.0210)
Subsidized Child Care Expenditure (000's)	0.0118	(0.0311)	0.0105	(0.0307)
Avg. Child Tax Credit	-0.0230	(0.0885)	-0.0265	(0.0892)
Average Tax Liability for a Family earning $25,000	0.0819	(0.0624)	0.0825	(0.0627)
Grade 2	-0.0177	(0.0983)	0.0559	(0.1171)
Grade 3	-0.0910	(0.1511)	0.0275	(0.1818)
Constant			-1.7094^{***}	(0.6323)
Mother/Child Type 1			0.2236	(0.2119)
Mother/Child Type 2			0.0525	(0.1410)
Mother/Child Type 3			0.1163	(0.2093)
Time-Varying Type 1			0.3400	(0.3785)
Time-Varying Type 2			-0.2030	(0.1908)
Observations	21750		21750	

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors are reported in parentheses. Missing data indicators are suppressed for brevity.

Table F.2.14: Logit: Attrition

	(1) OLS		(2) FIML	
Reading Score	-0.0133^{***}	(0.0017)	-0.0905	(0.0178)
Non-Cognitive Score	-0.0114^{***}	(0.0027)	-0.0631	(0.0207)
Mother Not Employed	0.0195^{***}	(0.0054)	0.1291	(0.0388)
Volunteering	-0.0154^{***}	(0.0054)	-0.0992^{**}	(0.0395)
Conference	-0.0118	(0.0099)	-0.0761^{***}	(0.0652)
Home Inputs	0.0097^{***}	(0.0027)	0.0716^{***}	(0.0264)
Decrease Siblings	0.0143	(0.0179)	0.1180^{***}	(0.1284)
Increase Siblings	0.0163	(0.0117)	0.1130^{***}	(0.0775)
Female	0.0099^{**}	(0.0048)	0.0732^{***}	(0.0364)
Mother's Age	-0.0591^{**}	(0.0245)	-0.2565^{***}	(0.1782)
Mother's Age Sq.	0.0031	(0.0033)	-0.0012^{***}	(0.0253)
Some College	0.0145^{**}	(0.0068)	0.0975^{***}	(0.0480)
Bachelors or Higher	0.0251^{***}	(0.0074)	0.1607^{***}	(0.0569)
Household Income	-0.0030	(0.0061)	-0.0126^{***}	(0.0453)
Black	0.0533^{***}	(0.0102)	0.3305^{***}	(0.0616)
Hispanic	-0.0001	(0.0085)	0.0063^{***}	(0.0620)
Other	0.0393^{***}	(0.0093)	0.2712^{***}	(0.0641)
Single Parent	-0.0314^{***}	(0.0080)	-0.2020^{***}	(0.0517)
Non-English Home Language	-0.0235^{***}	(0.0090)	-0.1513^{***}	(0.0637)
Hours of School-Related Leave	-0.0006^{***}	(0.0002)	-0.0050^{***}	(0.0017)
Avg. Unemployment Insurance Tax	0.0215^{***}	(0.0031)	0.1488^{***}	(0.0212)
Children per Child Care Center	0.0000	0.0000	-0.0002^{***}	(0.0002)
Maximum Weekly Benefit	-0.0001^{***}	0.0000	-0.0007^{***}	(0.0003)
Avg. Child Support (000's)	0.0139^{***}	(0.0033)	0.0938^{***}	(0.0238)
Per Cent Employed in Services	-0.0050^{***}	(0.0016)	-0.0358^{***}	(0.0126)
Subsidized Child Care Expenditure (000's)	0.0018	(0.0023)	0.0112^{***}	(0.0182)
Avg. Child Tax Credit	-0.0355^{***}	(0.0063)	-0.2436^{***}	(0.0446)
Average Tax Liability for a Family earning \$25,000	0.0307^{***}	(0.0042)	0.2466^{***}	(0.0363)
Grade 2	0.0484^{***}	(0.0063)	0.3355^{***}	(0.0536)
Constant	1.3950^{***}	(0.0588)	-0.0268^{***}	(0.4327)
Mother/Child Type 1			-0.2026^{***}	(0.1232)
Mother/Child Type 2			-0.3795^{***}	(0.0931)
Mother/Child Type 3			-0.3575^{***}	(0.1557)
Time-Varying Type 1			0.3953^{***}	(0.1684)
Time-Varying Type 2			-0.4449^{***}	(0.1386)
Observations	24750		24750	

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors are reported in parentheses. Missing data indicators are suppressed for brevity.

Table F.2.15: Continuous: Initial Reading Skills

	(1) OLS		(2) FIML	
Female	0.1650***	(0.0239)	0.1127***	(0.0255)
Black	−0.0208	(0.0431)	−0.0733	(0.0472)
Hispanic	−0.2117***	(0.0328)	−0.2216***	(0.0357)
Other	0.2565***	(0.0414)	0.1615***	(0.0435)
Mother Not Married at Birth	−0.2128***	(0.0312)	−0.1658***	(0.0312)
Mother's Age at First Birth	0.0457***	(0.0174)	0.0267	(0.0172)
Mother's Age at First Birth Squared	−0.0056*	(0.0033)	−0.0031	(0.0032)
Birth Weight	0.0561***	(0.0092)	0.0298***	(0.0087)
No. of older siblings	−0.0886***	(0.0130)	−0.0860***	(0.0159)
Birth Order	−0.0150	(0.0175)	−0.0283	(0.0181)
Some College	0.2832***	(0.0310)	0.2577***	(0.0334)
Bachelors or Higher	0.6347***	(0.0357)	0.5422***	(0.0404)
Constant	−0.1908	(0.2338)	−0.7284***	(0.2276)
Mother/Child Type 1			2.7617***	(0.0745)
Mother/Child Type 2			1.0359***	(0.0276)
Mother/Child Type 3			0.9598***	(0.1085)
Observations	8550		8550	

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors are reported in parentheses. Missing data indicators are suppressed for brevity.

Table F.2.16: Continuous: Initial Math Skills

	(1) OLS		(2) FIML	
Female	−0.0329	(0.0210)	−0.0933***	(0.0234)
Black	−0.3235***	(0.0377)	−0.3563***	(0.0434)
Hispanic	−0.3001***	(0.0297)	−0.2979***	(0.0324)
Other	0.0732**	(0.0334)	0.0124	(0.0368)
Mother Not Married at Birth	−0.1576***	(0.0285)	−0.1116***	(0.0286)
Mother's Age at First Birth	0.0404**	(0.0157)	0.0210	(0.0160)
Mother's Age at First Birth Squared	−0.0044	(0.0029)	−0.0017	(0.0030)
Birth Weight	0.0678***	(0.0083)	0.0421***	(0.0080)
No. of older siblings	−0.0088	(0.0119)	−0.0056	(0.0146)
Birth Order	−0.0124	(0.0156)	−0.0219	(0.0169)
Some College	0.2504***	(0.0288)	0.2240***	(0.0313)
Bachelors or Higher	0.6169***	(0.0318)	0.5450***	(0.0356)
Constant	0.0221	(0.2187)	−0.5979***	(0.2130)
Mother/Child Type 1			2.3719***	(0.0380)
Mother/Child Type 2			1.2554***	(0.0276)
Mother/Child Type 3			1.1858***	(0.1246)
Observations	8550		8550	

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors are reported in parentheses. Missing data indicators are suppressed for brevity.

Table F.2.17: Continuous: Initial Non-Cognitive Skills

	(1) OLS		(2) FIML	
Female	0.4629***	(0.0198)	0.4278***	(0.02040)
Black	−0.1443***	(0.0383)	−0.1565***	(0.03950)
Hispanic	0.0104	(0.0283)	0.0154	(0.02900)
Other	0.0653**	(0.0303)	0.0434	(0.03050)
Mother Not Married at Birth	−0.1958***	(0.0284)	−0.1712***	(0.02820)
Mother's Age at First Birth	0.0800***	(0.0150)	0.0695***	(0.01480)
Mother's Age at First Birth Squared	−0.0135***	(0.0028)	−0.0120***	(0.00270)
Birth Weight	0.0379***	(0.0078)	0.0245***	(0.00760)
No. of older siblings	0.0354***	(0.0110)	0.0374***	(0.01160)
Birth Order	0.0681***	(0.0146)	0.0647***	(0.01480)
Some College	0.0009	(0.0279)	−0.0133	(0.02810)
Bachelors or Higher	0.1535***	(0.0296)	0.1225***	(0.03020)
Constant	−2.1321***	(0.2080)	−2.5011***	(0.20340)
Mother/Child Type 1			1.1453***	(0.05190)
Mother/Child Type 2			0.7496***	(0.04190)
Mother/Child Type 3			0.7706***	(0.09730)
Observations	8550		8550	

Notes: Observations have been rounded to comply with the requirements of using the restricted-use dataset. Standard errors are reported in parentheses. Missing data indicators are suppressed for brevity.

G.2.1 Figures

Figure G.2.1: Parents' Report on How Well the School Makes Them Aware of Opportunities to Volunteer

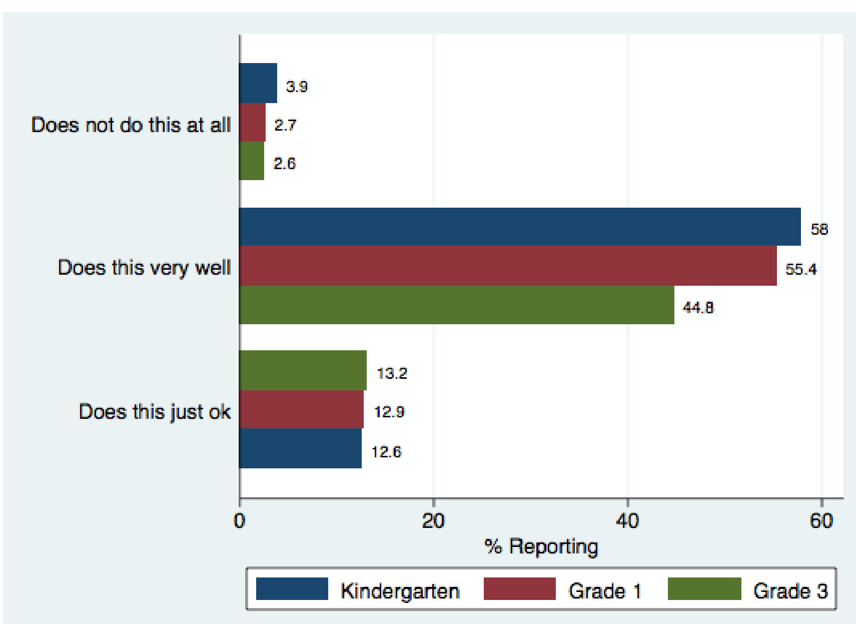
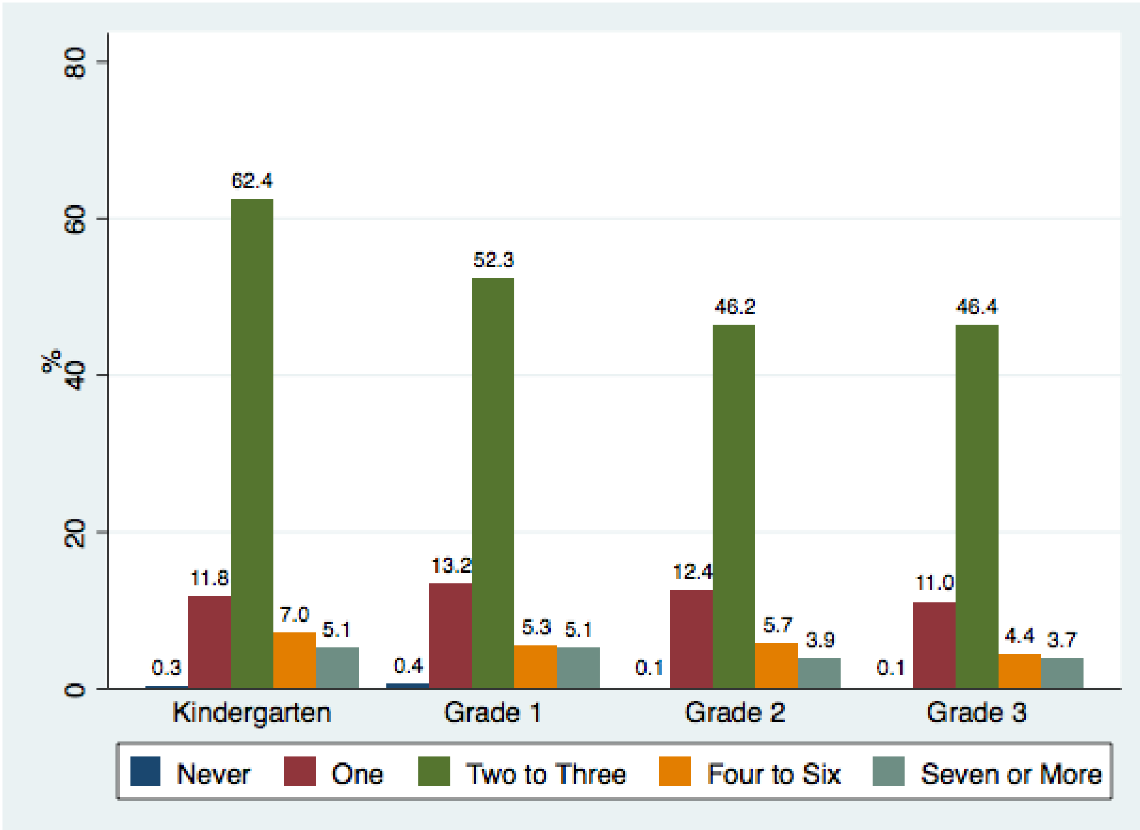


Figure G.2.2: Schools' Report on the Frequency of Parent-Teacher Conferences



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